Prospects & Applications of Artificial Intelligence in Livestock Sector

First Edition

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Prospects & Application of Artificial Intelligence in Livestock Sector

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MESSAGE

National Institute of Agricultural Extension Management (MANAGE), Hyderabad is an autonomous organization under the Ministry of Agriculture & Farmers Welfare, Government of India. The policies of liberalization and globalization of the economy and the level of agricultural technology becoming more sophisticated and complex, calls for major initiatives towards reorientation and modernization of the agricultural extension system. Effective ways of managing the extension system needed to be evolved and extension organizations enabled to transform the existing set up through professional guidance and training of critical manpower. MANAGE is the response to this imperative need. Agricultural extension to be effective, demands sound technological knowledge to the extension functionaries and therefore MANAGE has focused on training program on technological aspect in collaboration with ICAR institutions and state agriculture/veterinary universities, having expertise and facilities to organize technical training program for extension functionaries of state department.

Artificial Intelligence has already begun to revolutionize traditional farming practices, and its impact on livestock management is poised to be equally transformative. AI is revolutionizing the livestock sector, but the potential applications are vast and varied. As technology continues to evolve, it's crucial for stakeholders in the livestock industry to embrace innovation and explore ways to integrate AI solutions into their operations.

By harnessing the power of AI, we can enhance animal welfare, improve efficiency, and ensure the sustainability of livestock farming for future generations. I'm excited about the possibilities that lie ahead and look forward to witnessing the continued advancement of AI in agriculture.

This e-book covers an array of subjects, Prospects & Application of Artificial Intelligence in Livestock Sector. I would like to extend my appreciation to, GADVASU, Ludhiana & EAAS Centre, MANAGE, Hyderabad for the tremendous effort in compiling this ebook. I also thank the authors, editors, and designers who have contributed to this ebook creation.

Dr. P. Chandra Shekara
(Director General, MANAGE)

FOREWORD

The integration of artificial intelligence (AI) into various sectors has proved to be revolutionary and reshaping the way of living. In the realm of agriculture, particularly in the livestock sector, AI holds immense promise, offering solutions to age-old challenges while paving the way for unprecedented advancements.

The book entitled "Prospects & Applications of Artificial Intelligence in Livestock Sector," is a testament to the boundless opportunities that AI presents for optimizing livestock production and management, enhancing animal welfare, and bolstering agricultural sustainability.

Authored by experts at the forefront of agricultural innovation, this comprehensive volume offers a panoramic view of the current landscape of AI applications in the livestock sector, while also providing valuable insights into future prospects and emerging trends. From precision animal monitoring and predictive analytics to automated husbandry practices and genomic selection, each chapter delves into the myriad ways in which AI is revolutionizing the way we raise, manage, and care for livestock.

As we stand on the precipice of a new era in agriculture, characterized by unprecedented technological advancements and evolving consumer demands, the knowledge encapsulated within these pages serves as a guiding light for stakeholders across the agricultural spectrum. Whether you are a farmer seeking to optimize production efficiency, a researcher exploring the frontiers of AI-driven innovation, or a policymaker shaping the future of agricultural policy, this book offers invaluable insights that will inform and inspire your endeavors.

I commend the authors for their dedication to shedding light on this critical intersection of agriculture and technology, and I am confident that their collective expertise will serve as a catalyst for continued innovation and progress in the livestock sector. May this book ignite a spark of curiosity, provoke thought-provoking discussions, and ultimately pave the way for a more sustainable and prosperous future for agriculture and society at large.

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PREFACE

The integration of artificial intelligence (AI) into various sectors has revolutionized industries, promising unparalleled advancements and efficiency. Among these, the livestock sector stands as a domain ripe for innovation and transformation. In this book, "Prospects and Applications of Artificial Intelligence in Livestock Sector," we embark on a journey through the intersection of cutting-edge technology and traditional husbandry practices.

Livestock farming has been a cornerstone of human civilization, providing sustenance, livelihoods, and economic stability for communities worldwide. However, the challenges facing this sector are multifaceted and ever-evolving. From optimizing production processes to ensuring animal welfare and addressing environmental concerns, stakeholders in the livestock industry are constantly seeking novel solutions. By harnessing the power of AI technologies such as machine learning, computer vision, and predictive analytics, we can delve deeper into the complexities of livestock management, making informed decisions that enhance productivity, sustainability, and animal welfare.

This book serves as a comprehensive guide to the potential of AI in the livestock sector. Through a collection of insightful chapters authored by experts and practitioners in the field, readers will explore diverse applications spanning animal health monitoring, precision nutrition, smart farming techniques, and beyond. Moreover, we delve into the ethical considerations, regulatory frameworks, and socio-economic implications surrounding the adoption of AI in livestock farming. As we navigate through these pages, readers will gain a holistic understanding of how AI is reshaping the landscape of the livestock sector.

The Editors extend gratitude to all the contributors who have shared their expertise and perspectives, making this book a testament to the collaborative efforts driving innovation in livestock sector. Our hope is that this compilation inspires further exploration, discussion, and action towards a more sustainable and resilient future for livestock farming.

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Introduction to Artificial Intelligence and its Applications in Livestock Sector

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Introduction

In recent years, the application of artificial intelligence (AI) in various sectors has gained significant attention. The livestock sector, which plays a crucial role in food security, livelihood generation and employment creation has also started leveraging AI technologies to enhance livestock productivity, animal health, and overall management practices. The livestock sector is essential for providing a stable and sustainable food supply to meet the growing global demand. However, managing livestock effectively requires efficient monitoring, disease control, and genetic improvement strategies. With advancements in AI technologies, the livestock sector can benefit from data-driven decision-making, automation, and predictive analytics to address these challenges. This chapter explores the diverse applications of AI in the livestock sector, including applications in livestock health, production, reproduction, products, welfare and statistics. The chapter also provide insights on precision livestock farming enabling more precise and sustainable farming practices. The chapter highlights the potential benefits and challenges associated with AI adoption and discusses future trends in this rapidly evolving field.

Applications for Livestock Health

Robotic Imaging

The EQUIMAGINE robotics-controlled imaging system, which has clinical and research applications for both animal and human medicine, is used for the first time by a veterinary teaching hospital in the world at New Bolton Centre of the Penn State University's Veterinary College. The New Bolton

Centre also provides robotically controlled computed tomography (CT) scans of various body areas on standing patients. The EQUIMAGINE system at the New Bolton Centre offers various benefits, viz. the patient remains unsedated, less time required for obtaining the scan, high calibre images, ease in interpretation of results.

Canine Patient Simulator

The development of the first robotic dog simulator in the world for use in veterinary training in 2010 resulted in the opening of a new simulation centre at Cornell's College of Veterinary Medicine. Modern educational technologies like these pet simulators are employed to instruct students. These adhere to ethical and welfare standards for animals. With the use of these gadgets, students can efficiently learn without endangering the actual animal. In addition to two fully furnished exam rooms, two rooms for live video-feed observation and debriefing, and space for storage and constructing additional models, such a new robotic cat and a more sophisticated dog, Cornell's new simulation centre has all of these features.

Thermal Imaging Cameras

A helpful and convenient tool for clinical examination of livestock is a thermal imaging camera. These cameras offer a dependable non-contact technology that may be deployed rapidly. Animals do not need to be touched, be sedated, or be exposed to radiation in order to use a thermal imaging camera. A further benefit of employing a thermal imaging camera over other diagnostic equipment like X-ray, ultrasound, and MRI scanners is that the owner of the animal may see the preliminary results right away.

Anti-Stress Ear Tag for Cattle

The anti-stress ear tag increases production across the herd through effective, real-time animal status monitoring. The 200 parameters it analyses at once aid in accuracy in heat detection and accurate recommendations for insemination timing, early disease detection and for improved health management, knowledge of rationing and nutrition concerns, environmental factor detection and analysis for best decision-making, increased herd-wide surveillance, effective herd management includes timely reporting, etc.

Pig Respiratory Disease Package

A microphone installed in the pigsty and a sound analyzer connected to a computer make up the package for pig respiratory disease. The microphone picks up any changes in the pigs' voices, coughing, and respiratory distress and sends them to the analyzer. Any deviation from the expected sound is picked up. Since detecting even a slight variation in the sound of a pig's respiration is quite effective, diagnosing diseases 7 to 10 days prior to their beginning is helpful.

Applications for Livestock Production

Automatic Feed Manager

To predict the digestive process and its fermentation products based on sensor analyzer information, batch conditions, and other process data available in the data infrastructure, the major feed companies use predictive data analytics enabled by artificial production and a strong data infrastructure. The system can identify any changes in the feed's quality. Animal-specific diets can also be created based on metabolic tests done on the animal and its metabolic energy needs.

3D Cameras to assess Beef Cattle

The 3D cameras are typically employed to evaluate beef cattle. These cameras take a number of images, which are then tested to create an algorithm based on convolutional neural networks. The cameras evaluate the cattle using the body condition score (BCS) generated by the algorithm. The farmer is informed if a cow's body score is high or low.

Robo-Cams for Poultry

In the beginning, experiment farmers at the University of Georgia (UGA) used ground robots equipped with 2D and 3D sensors and cameras known as GOHBot, the Growout House Robot, to determine the viability of operating robots in poultry farms. The findings demonstrated that the presence of robotic systems in flocks had no detrimental effects on the birds. Although research is being conducted to automate robot cameras in poultry houses, their application is technically viable. Autonomous navigation may pave the way for robotic management of a variety of jobs, including continuously checking birds for illness and overall health to automating the removal of floor eggs in breeder houses.

Virtual Fences for Controlling Cattle

Smart collars are used to manage cattle in vulnerable riparian settings. According to certain research, cattle could be deterred from an area by using remote-controlled electrical and audio stimulation. They observed that although occasionally cattle may go the wrong direction, they quickly learn the association and avoid the region. The audio signals and minimal electric shock clubbed with GPS technology forms the complete setup of virtual fences.

The Dutch Cattle Expert System (veePRO)

The Dutch Cattle Expert System, created by the Dutch company Veepro, can recommend feed regimens, treatments, and circumstances for the welfare and health of livestock. By suggesting mating partners to enhance the genetic potential of progeny, it also aids in animal reproduction. The expert system also performs complicated analyses of maintaining animal health, the reproductive condition of specific animals or groups of animals, monitoring production, and recommending operational actions to be performed to enhance farm performance.

Applications for Animal Reproduction

Smart Neck Collar

Smart collars have a positive impact on fertility management in addition to health management. The sensor-based smart neck collars are devices for capturing several physiological characteristics. A software does the analysis to produce results based on the data collected. The heifers are inseminated using sexed semen, and the timing of insemination is a perfect example of a smart collar in action. The method has led to a significant reduction in the average calving interval, which has gone from 430 to less than 400 days and is expected to continue to drop.

Face Recognition Systems

Image analysis is the basis for how face recognition functions. Images of the animal's actual face and the pattern of spots on its body are evaluated to get results. It takes the system a little while to identify a specific animal. Giving computers the ability to track the precise amount of grain and water each cow receives makes what would normally take many weeks to do manually, occur virtually instantly. Dairy farmers can alter the level of nutrition by using the information gathered using this technology. The software keeps track of animal-related data and sends farmers the necessary alerts.

Cow Gait Analyzer or Pedometry

Pedometry is based on the measurements of steps each animal takes each day. The animals become restless and take more steps while they are in estrus. A cow in heat walks more frequently than on other days, which is studied by cow gait analyzer and aids in timely insemination of the animal in heat.

Intelligent Dairy Assistant

The livestock farmers can manage their dairy cows with the help of the Intelligent Dairy Assistant. It was created by a Dutch business to track the activity and movements of cows. A gadget is placed around the neck of the cow to record its movements as part of the IDA comprehensive solution for dairy management. In order to comprehend the behaviour of the animals in real time, a computer processes the sensor data using artificial intelligence (AI). The data that has been analysed reveals details about the animal's productivity and allows for projections of that output.

MSUES Cattle Calculator

The Mississippi State University Extension created the MSUES Cattle Calculator software, which is useful for people raising beef cattle. The programme has a reproductive calculator that can calculate the breeding season, calving, and breeding dates. Another calculator is available to evaluate animal performance, and it emphasises the adjusted weight amounts mostly related to birth, weaning, and yearling. The farm managers use the calculator to determine the right medicine dosages, frame scoring, and other factors.

Applications for Livestock Products

Robotic Milking Systems or Automatic Milking Systems (AMS)

AMS is based on the voluntary milking principle, which gives the cow the freedom to choose its own interval and duration between milkings. A milking unit, which consists of a milking machine, a teat position sensor (often a laser), a robotic arm for automatic teat-cup application and removal, and a gate system for managing cow traffic, make up this system. A cow tag sensor on the cow reads the code when cow feels like it needs to be milked and sends the signal to the control system. A robotic arm cleans the cow's teat as it enters the milking machine. Robotic procedures include fixing the cups of milking machine on the teats, milking the animal and post-milking spraying, and finally releasing the cow from the milking unit. After milking, cows are given concentrate feed as a reward for coming to the milking unit.

Robotic Hide Puller

The meat industry has recently included a robotic hide puller that operates on the principles of automation, artificial intelligence, and little human contact. As implied by its name, this device is used to extract hides from the carcasses of animals. A stainless-steel platform with built-in apron washers, knives/whizzers, sterilisers, drop trays, and drainage systems is included with the automatic hide puller. It lessens human contact while improving meat quality resulting in clean meat production. Additionally, meat quality is examined by motion cameras and intelligent cameras.

Smart Packaging

The Cortex System includes a camera that is similar to those found on most smartphones. The items are scanned by the camera as they move along the production line's conveyor belt. A smart packaging system called AMP Cortex is made up of a robot. It uses artificial intelligence (AI) to distinguish thousands of beverage and food cartons from the other items on the line. Cortex can distinguish between aseptic and gable-top cartons, as well as between cartons for almond milk and cartons for broth. It can also determine whether a product is recyclable or not.

Meat Supply Chain Optimization

The Artificial Neural Networks (ANN)-based algorithms can inspect and monitor the supply of meat and the tracking of commodities at every stage, making the process safer and more transparent. A perfect balance is established using ANN for meat supply from the place of production to place of consumption, thus reducing the demand-supply gap. Also, it makes forecasts regarding demand, supply, pricing and inventory, which prevents extra costs.

Applications for Animal Welfare

Robot Fish

The goal of a robot fish is to use contemporary robotics to mimic the original fish. It is a bionic robot that functions similarly to a swimming fish. The majority of artificial fish are created to resemble real fish that propel themselves using their body-caudal fins (BCF). The most crucial area for robot fish research and development is the improvement of their control and navigation, which will allow them to 'communicate' with their environment, travel along a specific course, and respond to commands by flapping their 'fins'. The robotic fish also act as fish lovers' companions. Additionally, more accurate models are being created to guide the development of fisheries research on robot fish.

Protection Assistant for Wildlife Security (PAWS)

Protection Assistant for Wildlife Security, or PAWS, is a recently created AI that uses information about prior poaching actions to generate patrol routes based on the likelihood that poaching will occur there. To prevent poachers from figuring out patrol patterns, these routes are randomly generated. As more data is frequently provided, PAWS can use machine learning, a subfield of AI, to continuously identify new insights/data.

Man's Best Friend 2.0

China shared its latest creation with the world "Domgy" which is robot dog. The pup bot can roll around a house, navigating obstacles, and it even knows to return to its charging station when battery power is low. Domgy can be controlled with smartphones and is equipped with facial recognition software that allows it to identify and greet the individual family members, learn how they like to be entertained, and also follow that owner's specific rules and preferences. It also acts as a security system as it contains a 5M camera in its head.

Minimizing Drug Testing on Animals

From its headquarters at John Hopkins University in Baltimore, Insilico Medicine develops new drugs and researches techniques to combat aging and disease. Instead of using live animals or humans, they use computers to test clinical trials through analysis and deep learning methods. The conditions are predicted using deep learning models and computer-based programs provide data as of recorded after a human trial. Given enough data, the systems are able to make accurate predictions without the need for animal testing, however, traditional testing is required in some cases.

Applications for Livestock Statistics

Vetel's Diagnostic Software

Vetel is a private company involved in creating diagnostic tools for the veterinarians. Now, in their new endeavour, the company has developed AI based radiography software for livestock disease diagnosis.

Sofie Cognitive Computing Tool

Sofie is the most advanced veterinary medical search tool available empowering veterinarians with instant online access to the most current, trusted, and credible veterinary medical information at the point of need. Sofie has one-click access to drug dosage calculators, toxicity calculators, trauma triage scores, and more with Vetcalculators.

Deep Mind for Record Keeping

DeepMind Technologies' helps to combine the best techniques from machine learning and systems neuroscience to build powerful general-purpose learning algorithms.

Deep Genomics

Deep Genomics serve patients by building and using artificial intelligence to discover and develop better treatments for genetic diseases, both rare and with large prevalence.

Precision Livestock Farming

Precision Livestock Farming (PLF) utilizes sensor technologies, machine learning algorithms, and big data analytics to monitor individual animals and optimize their production conditions. PLF offers benefits such as real-time monitoring of animal behaviour, health status, feed intake, and environmental parameters. These technologies enable early detection of health issues, improved feed efficiency, and enhanced animal welfare. Examples of PLF applications include automated milking systems, wearable sensors, and environmental monitoring systems.

Challenges and Ethical Considerations

While AI brings numerous benefits to the livestock sector, there are challenges and ethical considerations that need to be addressed. These include data privacy concerns, algorithm bias, potential job displacement, and ensuring animal welfare in AI-driven systems. It is crucial to establish robust governance frameworks, ethical guidelines, and transparent practices to ensure responsible AI adoption in the livestock industry.

Future Trends

The application of AI in the livestock sector is still evolving, and several promising trends are expected to shape its future. These include the integration of AI with Internet of Things (IoT) technologies for seamless data collection, the use of advanced robotics for automated tasks, the development of AI-powered decision support systems, and the application of AI in sustainable farming practices such as reducing greenhouse gas emissions.

Conclusion

The livestock sector stands to benefit significantly from the application of AI technologies. From precision livestock farming to disease management, animal behaviour analysis, and genetic improvement, AI offers opportunities to enhance productivity, animal welfare, and sustainability in livestock production. However, careful consideration of ethical and regulatory aspects is essential to ensure responsible and equitable use of AI in the livestock industry. With continued research and development, AI will continue to revolutionize the way we manage livestock, contributing to a more efficient and sustainable food system.

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Chapter 2
Precision Livestock Farming

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Introduction

Precision Dairy Farming (PDF) is the use of technologies to measure physiological, behavioural and production indicators of individual animals to improve management strategies and farm performance. It can also be defined as information and technology-based farm management system to identify, analyse and manage variability within farm management for optimum farm performance, profitability and sustainability. PDF, with specific emphasis on technologies for individual animal monitoring, aims for an ecologically and economically sustainable production of milk with secured quality, as well as a high degree of consumer and animal protection. Precision farming is based on information technology, which enables the producer to collect information and data for better decision making. PDF refers to the use of technologies that makes farmers less dependent on human labour, supports them in their (daily) management, and helps them to improve their farm profitability.

Economic livestock farming

Due to academic studies, the requirements of an animal are well known for each phase of its life and individual physical demands. These requirements allow the precise preparation of an optimal feed to support the animal. The requirements are oriented on the required nutrition – providing more nutrition than required make no economic sense, but providing less nutrients can be negative to the health of the animal. PLF starts with consistently collecting information about each animal. For this, there are several technologies: unique ID, electronic wearables to identify illness and other issues, software, cameras, etc. Each animal requires a unique number (typically by means of an ear tag).

This can be utilized through a visual ID, passive electronic ID tag or an active electronic ID tag.

Electronic wearable devices such as an active smart ear tag can get data from individual animals such as temperature and activity patterns. This data can be utilized in identification of illness, heat stress, estrous, etc. This enables individualized care for the animals and methods to lower stress upon them. The end result is judicious use of drug treatments and nutrition to bolster healthy growth. This provides livestock producers with the tools to identify sick animals sooner and more accurately. This early detection leads to reduction in costs by lowering re-treatment rate and death loss, and getting animals back to peak performance faster. Data recorded by the farmer or collected by sensors is then gathered by software. Although there has been software used that was run on a single computer, it has become more common for the software to connect to the internet, so that much of the data processing can happen on a remote server. Having the software connected to the internet can also make it easier to look up information about a particular animal.

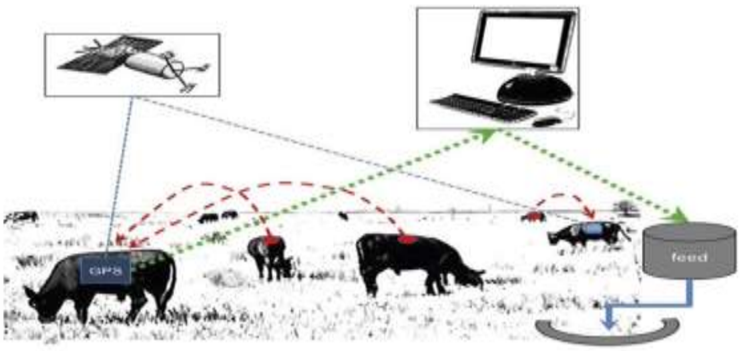

Fig 1: GPS enabled smart farming

Applications of Precision Livestock Farming

Robotic Milker: In automatic milking, a robotic milker can be used for precision management of dairy cattle. The main advantages are time savings, greater production, a record of valuable information, and diversion of abnormal milk. Brands of robotic milkers include Lely and DeLavel.

Milk yield and milk electrical conductivity: Significant changes in milk yield and electrical conductivity can be observed as early as 10 days before diagnosis of an adverse health event. Though, PDF technologies may alert the dairy farmer at an earlier stage giving time advantage, they do not indicate what type of disease is onset. This approach also fails to detect small changes in milk yield or milk electrical conductivity that are often associated with the onset of a health disorder. Further, the electrical conductivity along with other information (e.g., milk yield, milk flow, number of incomplete milking) may increase accuracy of detection and ability to determine early onset of mastitis.

Automatic Feeders: An automatic feeder is a tool used to provide feed to cattle. It is composed of a robot (either on a rail system or self-propelled) that will feed the cattle at designated times. The robot mixes the feed ration and will deliver a programmed amount.

Activity Collars: Activity collars gather biometric data from animals. Some wearable devices help farmers with estrous detection, as well as other adverse health events or conditions. The use of GPS 'collar' for livestock including dairy animals has become widespread in the last two decades. This has opened the possibility of recording detailed position information for long periods of time, thus allowing a more complete understanding of the habits and causes of spatial distribution of ruminants. Further, given the history of prices in electronic technology, it is very likely that with the proper investment in research and development, we can have cost effective herd information systems with which we will be able to see where and how all of our animals are and what they are doing at any time.

Inline Milk Sensors: Inline milk sensors help farmers identify variation of components in the milk. Some sensors are relatively simple technologies that measure properties such as electrical conductivity, and others use automated sampling and reagents to provide a different measure to inform management decisions.

Rumen pH: Measurement of ruminal fluid pH is a reliable and accurate diagnostic test for ruminal acidosis. Individual dairy cows exhibit tremendous variation in the degree of acidosis they experience, even when fed and managed similarly. However, rumen pH could be used as an instrument steering rumen fermentation for optimal production and health of cows. Continuous monitoring of ruminal pH is possible through wireless telemetry which has the capacity to accurately detect subacute ruminal acidosis.

Rumination: The percentage of cows ruminating at any given time has been considered by many people as an indicator of herd rumen health, as ruminal pH is affected by the amount of time the cow spends ruminating. Technologies for the automatic capture of rumination would allow for easy detection of changes in both individual cow and herd rumen health, and thus allow for the diagnosis of acute acidosis. An example of this is an electronic rumination monitoring system, which would allow for easy detection of changes in both the individual cow, as well as herd rumen health, and thus, allow for the detection of a bout of acidosis.

Fig 2: Monitoring of dairy animals through Artificial Intelligence

Rumen temperature: The use of ruminal temperature in field situations depends on future development of a practical and cost effective intra-ruminal wireless telemetry temperature sensing device. They act as rumen sensors to measure temperature, pressure/motility and pH in rumen.

Body condition score (BCS): Only a few dairy farmers have integrated BCS based on visual evaluation in their daily management strategy mainly because it is fairly time consuming and subjective. There is a strong relationship between the angles measured by video imaging and the BCS as determined by trained evaluators. Further, measuring Backfat Thickness (BFT) by ultrasound is of added value compared with other body condition scoring systems because it is objective and precise. Ongoing research on automation of body condition scoring suggests that it must be incorporated into decision support systems in the near future to aid producers in making operational and tactical decisions.

EID / RFID / Electronic Identification / Electronic Ear Tages: Radio Frequency Identification (commonly known as RFID or EID) is applied in cattle, pigs, sheep, goats, deer and other types of livestock for individual identification. There is currently a growing trend of RFID or EID becoming mandatory for certain species. For example, Australia has made EID compulsory for cattle, as has New Zealand for deer, and the EU for sheep and goats. EID makes identification of individual animals much less error-prone. RFID enhances traceability, but it also provides other benefits such as reproduction tracking (pedigree, progeny, and productivity), automatic weighing, and drafting.

Smart Ear Tags: Cattle hide their symptoms of illness from humans due to their predatory response. Smart cattle ear tags constantly gather behavioural and biometric data from cattle, allowing managers to see the exact animals that need more attention regarding their health. Smart ear tagging has been shown to be effective in identifying illness earlier and more accurately than traditional visual monitoring.

Automated Weight Detection Cameras: Automated weight detection cameras can be used to calculate the pig's weight without a scale. These cameras can have an accuracy of less than 1.5 kilograms.

Microphones to Detect Respiratory Problems: In the swine industry, the presence of respiratory problems must be closely monitored. There are multiple pathogens that can cause infection, however, enzootic pneumonia is one of the most common respiratory diseases in pigs caused by *Mycoplasma hyopneumoniae* and other bacteria. This is an airborne disease that can be easily spread due to the proximity of the pigs in the herd. Early detection is important in using fewer antibiotics and minimizing economic loss due to appetite loss of pigs. A common symptom of this is chronic coughing. A microphone can be used to detect the sound of coughing in the herd and raise an alert to the farmer.

Climate Control: Thermal stress is connected to reduced performance, illness, and mortality. Depending on geographical location, and the types of animals will require different heating or ventilation systems. Broilers, laying hens, and piglets like to be kept warm. Sensors can be used to constantly receive data about the climate control in the livestock houses and the automatic feeding systems. The behaviour of animals can also be monitored.

Poultry Industry: In the poultry industry, unfavourable climate conditions increase the chances of behavioural, respiratory, and digestive disorders in the birds. Thermometers should be used to ensure proper temperatures, and animals should be closely monitored for signs of unsatisfactory climate.

Infra-Red Thermography (IRT): Infrared thermography (IRT) absorbs infrared radiation and generates images based on the amount of heat generated. Infrared energy can be measured using an infrared camera and a specially developed analysing software program. A major advantage of the method is that it does not require direct physical contact with the surface monitored, thus allowing remote reading of temperature distribution.

1.As a diagnostic tool. In these cases, IRT becomes a physiological imaging method. The difference of 1 °C between two anatomically symmetric regions indicates their inflammation

2.To enhance the possibilities of physical examination. In these cases, thermography can determine suspicious areas where the heat is increased or decreased.

3. In wellness programmes. In this case, animals are monitored on a routine basis once a week. Thermography can be used to detect subclinical problems, as clinical changes occur two weeks after thermographic changes

Total Mixed Ration (TMR): Total Mixed Ration (TMR) can be described as a mixture of both the roughage and the processed ingredients, formulated and mixed to supply the cows' requirements, in a form that precludes selection. The TMR technology offers many advantages that lead to increased milk production.

1. Improved rumen fermentation. Cows have continuous access to a complete and balanced ration throughout the day. Thus, they tend to consume smaller but more meals per day, spread out evenly during their day. This prevents slug feeding that overloads the rumen with nutrients and unbalances the process. In contrast, rumen processes are optimized, digestibility improves, pH stabilizes and digestive upsets are minimized. This is because with each meal, the rumen microflora receives a balanced mix of all nutrients required for fermentation towards a desirable outcome.

2. Increased dry matter intake. As digestive functionality and health are sustained at high levels, and in conjunction with continuous feed availability, cows consume more dry matter. Not only that, but they cannot pick out undesirable (unpalatable, dusty, etc.) ingredients, leading to much better efficiency of feed utilization and less residual feed. In addition, as the dry matter intake is easily monitored, nutrition can be easily adjusted to match

genetic potential and actual performance, not to mention the ability to perform quick nutrition challenge on-farm trials.

3. Enhanced milk production. As it can be anticipated, a healthy cow with a functioning rumen, free of digestive disorders, and exhibiting maximal feed intake will produce more milk.

Conclusion

Precision Livestock farming in India is still restricted to some of the farmers but there are tremendous opportunities for improvements in individual animal and herd management on dairy farms. Further research and extension activities needs to be promoted in the field of Precision Livestock farming to augment farmers income.

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Chapter 3
Big Data and Statistics

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Introduction

The science of statistics has been known to us since long as a science of analysis of data; however, till the time, we had mere speculations that there will come a day when the amount of data will grow so huge that we will require a new discipline to describe the methods for handling it. The statistics has been referred to as 'the science of data' and includes the processes required to handle the data from collection till inference and forecasting.

While the classical statistical techniques have been found sufficient to deal with and draw inferences from the amount of data available until a while ago, the scenario completely overturned with rapid digitalization of data and technological advances in uses of sensors to automatically acquire the rapid, real-time data with convenience over the internet/cloud. The advent of smart devices, IoTs and desire of automation led to exponential increase in amount of data being produced. The 'Big Data' is a term used to describe the huge bulks of data being generated, stored, and shared every day. This big data can come from a variety of sources, such as social media, sensor networks, financial transactions, and molecular information. To handle such data a new branch of science emerged gradually and it is come to be known as 'Data Science'. While the roots of data science still remain in the statistics, it also draws heavily from electronics, sensors, computer science, programming, machine learning, networking, and cloud computing, and thus is in spirit a multi-disciplinary stream.

With the added volume, there also came the complexity and impurity in the data, such that the raw data in aften referred to as being dirty, and requires to be cleaned. Further, to handle such the rigidly defined statistical procedures may also not always be suitable, so flexibility in procedures in terms of algorithms were required. The multidimensional data as such needs further processing to limit the dimensionality and break the collinearity. And last but not the least all of these will require a lot of computational resources and a programming approach as each dataset may have unique characteristics. Further one will require to use sub-sampling techniques from multi-dimensional sampling space to economize on the required computational resources and time.

Variable and Data

Data is the most important asset for any organization as it allows to set baseline, measure progress, predict outcomes, make decisions, and set future goals. Importance of the data can be understood from the fact that most of the business giants try to access and analyse data for the development, launch and marketing of their products and services. Even before the development of big data analytics, big companies knew the importance of data for their business and they used to store tons of data without knowing much about the analysis and interpretation of the data, even though it used to cost them heavily.

Data is essentially the values and observations recorded under a variable. Where a variable is a defined characteristic, which has a set protocol of its measurement/ observation. So, a collection of a jumble of figures measuring different characteristics cannot be called a data.

The data derived from the real world is 'Dirty,' as it is aften:

- Incomplete: lacking certain attributes of interest, or containing only aggregate data
- Noisy: containing errors or outliers, collinearity, confounding etc.
- Inconsistent: containing discrepancies in codes or names, typographical and instrumental errors, out of the bound records etc.

Thus, the raw data needs to be cleaned, prior to its analytical uses for optimal analysis and reliable outputs. The process of making the data usable for further analysis is called data processing and it involves:

- Data cleaning: Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- Data integration: Integration of multiple databases, data cubes, or files
- Data transformation: Normalization and aggregation
- Dimensionality reduction: Obtains reduced representation in volume but produces the same or similar analytical results
- Data discretization: Part of data reduction but with particular importance, especially for numerical data

Statistics

Statistics is a stream of mathematics that deals with the collection, analysis, interpretation, and presentation of data. It is used to make sense of data and to draw conclusions about the world. Statistics is a vast field, and there are many different statistical techniques that can be used. Some of the most common statistical techniques include:

- Descriptive statistics: Descriptive statistics are used to summarize data and to describe the main features of a data set. This kind of analysis is called exploratory analysis. For example, descriptive statistics can be used to calculate the mean, median, and standard deviation of a data set.
- Inferential statistics: Inferential statistics are used to make inferences about a population based on a sample. For example, inferential statistics can be used to estimate the probability of winning a lottery or to predict the outcome of an event.
- Probability: Probability is the study of chance. It is used to quantify the likelihood of events happening. For example, probability can be used to calculate the odds of winning a game of roulette or the probability of getting a certain score on a test.
- Hypothesis testing: Hypothesis testing is a statistical procedure used to test the validity of a hypothesis. A hypothesis is a statement about the population that is being studied. For example, a hypothesis might be that the average height of men is taller than the average height of

women. Hypothesis testing can be used to determine whether the hypothesis is supported by the data.

- Modelling: Modelling is the process of creating a mathematical expression of a real-world event. Models can be used to make predictions about the system or to understand the system's behaviour. For example, a predictive model can be used to predict the weather or to understand the spread of a disease.
- Statistics is a powerful tool that can be used to solve a wide variety of problems. It is used in a variety of fields, including business, economics, healthcare, and social science. Statistics serves as a fundamental component in both AI and Data Science.

Big Data

Big data is the term used for huge composite data sets collected from different sources. The collection, storage and processing of such data is not possible using the conventional tools due to its immense complexity and sheer quantity. The term "Analytics" is the scientific process of systematic computational analysis of data for discovering, interpreting, and communicating the meaningful patterns hidden in data which may not otherwise be detected. The term "Big Data" was first used by Michael Cox and David Ellsworth in 1997 to describe large volumes of scientific data visualization in an article in the ACM digital library. Big data is characterized by its three V's: volume, velocity, and variety.

- Volume: Big data is often very large in terms of the amount of data that is being generated. For example, a single day of next generation DNA sequencing activity can generate terabytes of data.
- Velocity: Big data is often generated very quickly. For example, sensor networks can generate data at a rate of millions of events per second.
- Variety: Big data can come in a variety of formats, including structured, semi-structured, and unstructured data.

Additionally, some more characteristics are also attributed to the big data, like

- Variability: In addition to the increasing velocities and varieties of data, data flows are unpredictable – changing often and varying greatly.
- Veracity: Veracity refers to the quality of data. Because data comes from so many different sources, it's difficult to link, match, cleanse and transform data across systems.

The sheer amount of the information, heterogenous source and formats, inter-relationships between variables, confounding, and multiple dimensionalities are few among many complications associated with the big data. The challenges of big data include:

- Data storage: Big data can be very difficult to store, as it often requires specialized hardware and software.
- Data processing: Big data can be very difficult to process, as it often requires specialized algorithms and computing resources.
- Data analysis: Big data can be very difficult to analyse, as it often requires specialized tools and techniques.

However, the added advantages of deriving the insights out of big data outpowers the hurdles associated with the uses of big data. The benefits of using big data include:

- New insights: Big data can be used to gain new insights into a variety of topics, such as customer behaviour, market trends, and fraud detection.
- Improved decision-making: Big data can be used to improve decision-making by providing businesses with more information to base their decisions on.
- Increased efficiency: Big data can be used to increase efficiency by automating tasks and identifying patterns that can be used to improve processes.

The future of big data is bright, as the amount of data being generated is only going to increase. This means that there will be even more opportunities to use big data to gain new insights, improve decision-making, and increase efficiency.

Here are some examples of how big data is being used today:

- Customer behaviour: Big data can be used to track customer behaviour, such as what products they purchase, how often they visit a website, and what pages they view. This information can be used to improve marketing campaigns and to provide better customer service.
- Fraud detection: Big data can be used to detect fraud, such as credit card fraud and insurance fraud. This is done by looking for patterns in data that are indicative of fraud.
- Healthcare: Big data can be used to improve healthcare by tracking patient data, such as medical records, lab results, and prescription history. This information can be used to improve diagnosis and treatment.
- Automation: Big data can be used to improve the existing solutions to optimize the available solutions to achieve better decision making and thus advance the level of automation in operations.
- Transportation: Big data can be used to improve transportation by tracking traffic patterns, weather conditions, and road conditions. This information can be used to optimize traffic flow and to improve safety.
- Environmental Monitoring: Big data can be to collect and analyse huge environmental databases, in order to monitor and manage natural resources, track climate change, and implement conservation plans, by helping scientists and policymakers.

These are just a few examples of how big data is being used today. Additionally, all of these can also be utilized in livestock operations to analyse and infer animal health, production, behaviour, welfare, farm operation automation, livestock product processing and many more apart from research advancement. As the amount of data being generated continues to increase, we can expect to see even more innovative uses for big data in the future.

Big Data in Veterinary Science

Big data started to have a major impact on veterinary science and livestock production, since the gradual adaptation of sensors and robots for farm automation. The increasing availability of data from a variety of sources, such as electronic health records, sensor networks, and social media, is providing new opportunities to improve animal health and welfare.

Here are some of the ways that big data is being used in veterinary science:

- Early detection of disease: can be used to identify patterns in data that could indicate the early onset of disease. This information can be used to develop preventive measures or to intervene early to improve the chances of a successful outcome.
- Personalized medicine: can be used to create personalized treatment plans for individual animals. This is done by considering the animal's genetic makeup, medical history, and other factors.
- Animal welfare: can be used to monitor animal welfare. This is done by tracking data such as food intake, activity levels, and social interactions. This information can be used to identify animals that are at risk of welfare problems and to intervene to improve their welfare.
- Disease surveillance: can be used to track the spread of disease. This is done by collecting data on animal movements and disease outbreaks. This information can be used to identify at-risk populations and to implement control measures.
- Research: The data derived from next generation molecular platforms and sensors can be used to conduct research into animal production, health, and welfare. This information can further be used to identify risk factors for disease and to develop new treatments and prevention strategies.
- Conservation: Animal migrations, population levels, and any threats to their habitats are monitored using satellite imaging, GPS tracking,

camera traps, and environmental sensor data. Big data also helps in tracking and monitor endangered species.

The use of big data in veterinary science is still in its early stages, but it has the potential to revolutionize the way that animal health is managed. As the amount of data available continues to grow, we can expect to see even more innovative uses for big data in the future. There are however, some challenges of using big data in veterinary science:

- Data quality: The quality of the data is essential for the success of any big data project. However, the data collected from animals can be noisy and incomplete. This can make it difficult to identify patterns and to draw accurate conclusions.
- Data privacy: The privacy of animal owners and their pets is a major concern. Any big data project must be designed to protect the privacy of the data collected.
- Data interpretation: The interpretation of big data can be challenging. This is because the data can be complex and there can be multiple interpretations of the same data.

Despite these challenges, the potential benefits of using big data in veterinary science are significant. As the technology continues to develop, we can expect to see even more innovative uses for big data in the future.

Statistics, Data Science and Artificial Intelligence

Artificial Intelligence (AI) is a field of mainly computer science that deals with the creation of intelligent agents, which are systems that can reason, learn, and act autonomously. AI is a more general field than statistics or data science, and it encompasses a wide range of techniques, including machine learning, natural language processing, and computer vision. In AI, statistical techniques are employed for model training, evaluation, and validation. Theoretical principles from statistics underpin many machine learning algorithms and guide decisions on model selection, hyperparameter tuning, and performance evaluation.

The data science is a multidisciplinary field that uses statistical methods, machine learning, and other techniques to extract knowledge from data, usually a big data. It is a more applied field, and it focuses on the use of data to solve real-world problems.

Statistics, data science, and artificial intelligence (AI) are all closely related fields that are concerned with understanding and handling huge data, making predictions, and building intelligent systems. These intertwined field continue to push the boundaries of innovation and develop solutions by building on one another's strengths. However, there are some key differences between the three fields. Here is a table that summarizes the key differences between statistics, data science, and AI:

Statistics	**Data Science**	**AI**
A branch of mathematics	A multidisciplinary field	A field of computer science
Focuses on the development and application of statistical methods	Focuses on the use of data to solve real-world problems	Focuses on the creation of intelligent agents
More theoretical	More applied	More general

Statistics for Big Data

Big data is a term used to describe the large and complex datasets that are generated by modern businesses and organizations. These datasets can be used to gain insights into customer behaviour, market trends, and other important factors. However, the sheer volume and complexity of big data can make it difficult to analyse using traditional statistical methods. This is where statistics for big data comes in. Statistics for big data is a field of study that focuses on the development and application of statistical methods for analysing large and complex datasets. These methods are designed to extract meaningful insights from big data that would otherwise be hidden.

There are a number of different statistical methods that can be used for big data analysis. Some of the most common methods include:

- Data mining: Data mining is a process of extracting patterns and relationships from large datasets. This can be used to identify trends, make predictions, and improve decision-making.
- Data Processing: The data processing as discussed earlier involves steps of Data cleaning, Data integration, Data transformation, Dimensionality reduction and Data discretization. All these steps in one way or other use one or more optimized statistical techniques to achieve data processing.
- Statistical modelling: Statistical modelling is a process of developing mathematical models that can be used to represent the relationships between variables in a dataset. This can be used to make predictions, test hypotheses, and understand the underlying structure of a dataset.

The use of statistics for big data is becoming increasingly important as the volume and complexity of big data continues to grow. By using statistical methods, organizations can gain insights into their data that would otherwise be hidden. This can lead to better decision-making, improved customer service, and increased profits.

Conclusion

The use of statistics for big data is still a relatively new but growing field. It is essential for organizations that want to gain insights from their data. By using statistical methods, organizations can improve their decision-making, customer service, and profits. As the volume and complexity of big data continues to grow, the use of statistics will become even more important.

Statista in 2020 estimated that the overall cash value of the big data market will reach USD 103 billion in 2023, and this figure could double by 2027.

The possibilities are endless. As the field of data science continues to evolve, so too will the role of statistics. As the amount of data that is being generated continues to grow, the need for these methods will only increase. The combination of big data and statistics is a powerful tool that can be used to solve a wide variety of problems. The field of data science is constantly evolving, and the demand for data scientists with a strong understanding of big data and statistics is only going to grow.

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Chapter 4
Introduction to Python, R, and MATLAB

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Introduction

Applications of artificial intelligence (AI) in various domains of biological sciences have heralded a new era and explored new ventures to serve mankind. Knowledge and skills in programming languages are pre-requisite to make use of AI and its diverse domains, namely, machine learning (ML) and deep learning (DL), in various facets of veterinary and animal sciences. Currently, two popular programming languages are Python and R–environment, which are extensively used in AI-ML-DL and for data science and analytics. Besides, MATLAB is a commercially available, proprietary programming language that has been developed by MathWorks. MATLAB is an abbreviation of "MATrix LABoratory". Several toolboxes (equivalent to specialized libraries/modules) are available in MATLAB that are extensively used for AI-ML-DL-related analysis and research.

The following information has been *accepted verbatim from our earlier invited talk* and practical hands-on "Understanding the scripting differences between R and Python" (Mukhopadhyay and Rana 2021).

R is an open-source programming environment and hence can be downloaded and installed freely. The R programming environment has a rich history, tracing its roots to the "S language", originally developed for statistical computing in the mid-1970s at Bell Laboratories. Ross Ihaka and Robert Gentleman created the open-source language R in 1995 as an implementation of the S programming language. The purpose was to develop a language that focused on delivering a better and more user-friendly way to do data analysis, statistics, and graphical models. At first, R was primarily used in academics and research, but lately, the enterprise world is discovering R as well. This makes R one of the fastest-growing statistical languages. Later, the open-source R project extended the capabilities of S while incorporating features of languages like LISP and Scheme. One of the main strengths of R is its huge community that provides support through mailing lists, user-contributed documentation, and a very active Stack Overflow group. The Comprehensive R Archive Network (CRAN) is a popular repository of curated R packages to which users can easily contribute. The current latest version of R for Windows is 4.3.1.

Python was created by Guido Van Rossem in 1991 and emphasizes productivity and code readability. Programmers that want to delve into data analysis or apply statistical techniques are some of the main users of Python for statistical purposes. It's a flexible language that is great to do something novel, and given its focus on readability and simplicity, its learning curve is relatively low. Similar to R, Python has packages as well. PyPi is the Python Package Index and consists of libraries to which users can contribute. Just like R, Python has a great community but it is a bit more scattered since it's a general-purpose language. Nevertheless, Python for data science is rapidly claiming a more dominant position in the Python universe: the expectations are growing and more innovative data science applications will see their origin here.

Conceptual differences between R and Python programming:

Many features of R are shared with Python: both are high-level, interpreted languages. Both languages provide a wide array of features and functions for common tasks, and both languages are buttressed by a staggering variety of additional packages for more specialized analyses. Superficially, much of their syntax is similar, though below the surface lie significant (and fascinating) differences.

Practically, the major difference between the two languages lies in what built-in features and functions are available, and what packages are available for download. Where Python is considered a "general purpose" language, R specializes in statistical analyses. R is probably the tool of choice to build a mixed nonlinear model for a large table of numerical values from a multifactorial experiment. Python is likely a better candidate to count potential promoter motifs in a large sequence set. R does support functionality for the types of string analyses covered in the section on Python (such as DNA sequence analysis and regular expressions), but these are currently easier to work with in Python. Python provides excellent data plotting through the matplotlib library, but R's ggplot2 library quickly became one of the dominant tools for data visualization since its initial release in 2005.

Where the analysis of biological data is concerned, both languages have grown rapidly. The Bioconductor packages in R provide many statistical bioinformatics tools, while BioPython focuses on some statistical methods and many sequence-oriented methods such as multiple sequence alignments. As of this writing, both languages appear to be heading toward a common feature set: relatively recent Python packages such as pandas, numpy, scipy, etc add functionality that has been present in R for decades, while R has grown in general functionality and popularity.

For most users, Python is a better "introductory programming experience," even if the experience is brief, for a couple of reasons. Python shares more similarities with other "mainstream" languages like Java, C, and C++ than does R, easing transference of concepts should one wish to continue on the programming journey.

Further, R contains a much larger menagerie of data types and specialized syntax for working with them, as well as multiple frameworks for things like variable assignment and object orientation. R is a remarkably flexible language. With so much flexibility comes both power and interesting ways of thinking about programming. While Python emphasizes the use of for-loops and if-statements to control program flow, R provides an alternative syntax for the manipulation of data through sophisticated logical statements (for-loops and if-statements are discussed late in this section).

Functions are equally important in Python, but in R they take on such significance that we are required to think about them at a higher level (as types

of data that can be operated on by other functions). For many of the statistical tasks in which R excels, the underlying interpreter code is highly optimized or parallelized so that analyses of millions or billions of data points can be completed quickly. Finally, many excellent packages are available only for R. Harris et al (2020) stated that Array programming provides a powerful, compact, and expressive syntax for accessing, manipulating, and operating on data in vectors, matrices, and higher-dimensional arrays. NumPy is the primary array programming library for the Python language.

Purpose

Either language is suitable for almost any data science task, from data manipulation and automation to ad-hoc analysis and exploring datasets. Users may leverage both languages for different purposes, e.g., conducting early-stage data analysis and exploration in R, then switching to Python when it's time to ship some data products. When getting started with R, a good first step is to install the amazing RStudio IDE.

R: Pros and Cons

Pro: Better data visualizations

Visualized data can often be understood more efficiently and effectively than raw numbers alone. R and visualization are a perfect match. Some must-see visualization packages are ggplot2, ggvis, googleV is, and rCharts.

Pro: R ecosystem

R has a rich ecosystem of cutting-edge packages and an active community. Packages are available at CRAN, BioConductor, and Github.

Pro: R lingua franca of data science

R is developed by statisticians for statisticians. They can communicate ideas and concepts through R code and packages, one doesn't necessarily need a computer science background to get started.

Con: R is slow

R was developed to make the life of statisticians easier, not the life of your computer. Although R can be experienced as slow due to poorly written code, there are multiple packages to improve R's performance: pqR, renjin and FastR, Riposte, and many more.

Con: R has a steep learning curve

R's learning curve is non-trivial, especially if you come from a GUI for your statistical analysis. Even finding packages can be time-consuming if someone is not familiar with it.

Python: Pros and Cons

Pro: IPython Notebook

The IPython Notebook makes it easier to work with Python and data. You can easily share notebooks with colleagues, without having them to install anything. This drastically reduces the overhead of organizing code, output, and notes files. This will allow you to spend more time doing real work.

Pro: A general-purpose language

Python is a general-purpose language that is easy and intuitive. This gives it a relatively flat learning curve, and it increases the speed at which you can write a program. In short, you need less time to code and you have more time to play around with it!

Furthermore, the Python testing framework is a built-in, low-barrier-to-entry testing framework that encourages good test coverage. This guarantees your code is reusable and dependable.

Pro: A multi-purpose language

Python brings people with different backgrounds together. As a common, easy-to-understand language that is known by programmers and that can easily be learned by statisticians, you can build a single tool that integrates with every part of your workflow.

Con: Visualizations

Visualizations are an important criterion when choosing data analysis software. Although Python has some nice visualization libraries, such as Seaborn, Bokeh, and Pygal, there are maybe too many options to choose from. Moreover, compared to R, visualizations are usually more convoluted, and the results are not always so pleasing to the eye.

Con: Python is a challenger

Python is a challenger to R. It does not offer an alternative to the hundreds of essential R packages.

Discussion

Elegance

Winner: Python

Python greatly reduces the use of parentheses and braces when coding, making it more sleek.

Learning curve

Winner: R

While data scientists working with Python must learn a lot of material to get started, including NumPy, Pandas, and matplotlib, matrix types and basic graphics are already built into base R.

Available Libraries

Winner: Tie

The Python Package Index (PyPI) has over 183,000 packages, while the Comprehensive R Archive Network (CRAN) has over 12,000. However, PyPI is rather thin on data science.

Machine learning

Winner: Python (but not by much)

Python's massive growth in recent years is partially fueled by the rise of machine learning and artificial intelligence (AI). While Python offers several finely-tuned libraries for image recognition, such as AlexNet, R versions can easily be developed as well.

The Python libraries' power comes from setting certain image-smoothing ops, which easily could be implemented in R's Keras wrapper, and for that matter, a pure-R version of TensorFlow could be developed. R's package availability for random forests and gradient boosting are outstanding.

Statistical correctness

Winner: R (by far)

Professionals working in machine learning who advocate for Python sometimes have a poor understanding of the statistical issues involved. R, on the other hand, was written by statisticians, for statisticians.

Parallel computation

Winner: Tie

The base versions of R and Python do not have strong support for multicore computation. Python's multiprocessing package is not a good workaround for its other issues, and R's parallel package is not either. External libraries supporting cluster computation are OK in both languages. Currently, Python has better interfaces to GPUs.

C/C++ interface

Winner: R (but not by much)

R's Rcpp is a powerful tool for interfacing R with C/C++. While Python has tools like swig for doing the same, it is not as powerful, and the Pybind11 package is still being developed. R's new ALTREP idea also has the potential for enhancing performance and usability; however, the Cython and PyPy variants of Python can sometimes remove the need for explicit C/C++ interface at all.

Object orientation, metaprogramming

Winner: R (but not by much)

Though functions are objects in both R and Python, R takes that more seriously, R's magic metaprogramming features (code that produces code), computer scientists ought to be drooling over R.

Language unity

Winner: Python (by far)

While Python is transitioning from version 2.7 to 3.x, this will not cause very much disruption. However, R is changing into two different dialects due to the impact of RStudio: R and the Tidyverse.

Linked data structures

Winner: Python (likely)

Classical computer science data structures, e.g. binary trees, are easy to implement in Python. While this can be done in R using its 'list' class, I'd guess that it is slow.

Popular Libraries and Packages:

Python

pandas to easily manipulate

datastatsmodels to explore data, estimate statistical models, and perform statistical tests and unit tests

SciPy and NumPy for scientific computing

Scikit-learn for machine learning

Matplotlib and seaborn to make graphics

Biopython for sequence analysis

R

dplyr, tidyr and data.table to easily manipulate data

stringr to manipulate strings

zoo to work with regular and irregular time series

ggplot2 to visualize

datacaret for machine learning

More people are switching from R to Python. Furthermore, there is a growing group of individuals using a combination of both languages when appropriate.

PypeR: a Python package that allows the R language to be called in Python using the pipe communication method. By running R through a "pipe", the Python program gains flexibility in sub-process controls, memory control, and portability across popular operating systems (Xia *et al.* 2010).

Measuring the similarity of graphs is a fundamental step in the analysis of graph-structured data, which is omnipresent in computational biology. ***Graph kernels*** have been proposed as a powerful and efficient approach to this problem of graph comparison, the first R and Python graph kernel libraries including baseline kernels such as label histogram-based kernels, classic graph kernels such as random walk-based kernels, and the state-of-the-art Weisfeiler-Lehman graph kernel (Sugiyama *et al.* 2018).

Comparison between important codes in R and Python

S No	Purpose	R	Python

1	Setting and getting the working directory	# Setting the working directory:
		setwd(Path/to/the/Directory)
		# Use forward-slash for Windows OS and back-slash for Linux OS
		
		# Retrieve the working directory:
		getwd()
		# "C:/Users/ADMIN/Documents"
			# Open Anaconda Prompt Jupyter notebook
			# Move to your folder in a specific Drive:http://localhost:8888/tree/OneDrive/Desktop/Example_Files_R_Python
			
			# Create New iPython NoteBook
			# Rename the ipynb: viz. Python_Codes_Example_05033021.ipynb
			
			# Setting/changing the working directory:
			import os
			os.chdir('H:\Class_Lectures')

S No	Purpose	R	Python
			# Get the current working directory: import os os.getcwd() # 'C:\\Users\\ADMIN\\Desktop' os.listdir() # To enlist all the files in the working directory The OS module in Python provides a way of using operating system-dependent functionality. The functions that the OS module provides allow you to interface with the underlying operating system that Python is running on – be that Windows, Mac, or Linux.

2	Check, Update all packages:	# Check installed packages
		installed.packages()
		
		# Get a list of all packages where an
			# Open Anaconda3 command prompt as Administrator:
			
			# Get the packages in the environment at

S No	Purpose	R	Python
		update is available old.packages() # Available packages available.packages() # Update all available packages, But this command will prompt for permission for each of the packages update.packages() # So, we can update all packages without prompts for permission update.packages(ask = FALSE)	C:\Path….\Anaconda3: conda list HTML # Update all packages conda update --all
3	Update TensorFlow	NA	# Create a new Conda virtual environment (Optional) conda create -n tensorflow_cpu pip python=3.7 # Activate the newly created virtual environment activate tensorflow_cpu

S No	Purpose	R	Python
4	Some important information	# Either <- or = for Right operand to left operand assignment; # -> for Left operand to right operand assignment Vector: same as an one dimensional an array List: it contains different sets that harbors items of different datatypes and size under one umbrella. The contents of a list is accessed by index or by name Matrix: a two-dimensional vector of fixed size, with same data types in all cells Array: a vector with one or more dimensions Data frame: a table with defined datatypes in different columns column	# List is a MUTABLE non-homogeneous data structure that stores the elements in a single row and multiple rows and columns: List can be represented by [ ] # Tuple is also a NON-MUTABLE non-homogeneous data structure that stores single row and multiple rows and columns: Tuple can be represented by ( ) # Dictionary is also a non-homogeneous data structure that stores key-value pairs: Dictionary can be represented by { } # Set data structure is also a non-homogeneous data structure but stores in a single row: Set can be represented by { } # Read:

S No	Purpose	R	Python

			https://www.geeksforgeeks.org/differences-and-applications-of-list-tuple-set-and-dictionary-in-python/
			
			# Import the package/library and also create an alias for the package
			import numpy as np
			
			# Now specify the function name within the package/library that you want to use:
			arr = np.array([1, 2, 3, 4, 5])
			
			print(arr)
			
			print(type(arr))
			
			# Give the module name and then after dot exclusively give the function name

5	Check the version of the package/library	sessionInfo() # To check the R version packageVersion("stats")	import pandas as pd pd.__version__

S No	Purpose	R	Python
		# Check the version of package <stats>	
6	Install some important packages in R & Python using conda	# In the R environment or R studio, use the following command: install.packages("plyr", "psych", "tm", dependencies=T)	conda install pillow, lxml, jupyter, matplotlib, opencv, cython
7	Creating vector	Vector_Name <- c("Ram", "Shyam") # We use concatenation 'c()' function to joining the objects	Tuple_Vector_Name = "Ram", "Shyam" List_Vector_Name = ["Ram", "Shyam"] There is no c() function in Python. We directly put the elements of a vector using a comma
8	Create DataFrame	DF_Name = data.frame(Name=c("AA", "BB", "CC", 'DD', 'EE', 'FF'), Age= c(20, 25, 30, 20, 20, 30), Ph.D.= c(TRUE, FALSE, T, T, TRUE, F))	import pandas as pd DF_Name_0 = pd.DataFrame({"Name" : ["AA", "BB", "CC", "DD", "EE", "FF"], "Age" : [20, 25, 30, 20, 20, 30], "Ph.D.": [True, False, True, "TRUE", "T", "FALSE"]}) DF_Name_0 # Note the difference between True and TRUE; as well as False, FALSE

S No	Purpose	R	Python

			# Importing pandas as pd
			import pandas as pd
			
			# Create a dictionary (i.e. a non-homogeneous data structure that stores key-value pairs) of lists
			dict = {"Name" : ["AA", "BB", "CC", "DD", "EE", "FF"],
			"Age" : [20, 25, 30, 20, 20, 30],
			"Ph.D.": ["True", "False", "True", "TRUE", "TRUE", "FALSE"]}
			
			DF_Name = pd.DataFrame(dict, index = [0,1,2,3,4,5])
			print(DF_Name)
			
			DF_Name1 = pd.DataFrame(dict)
			print("\n\n", DF_Name1)

9	Recognizing True and False	True and False can be represented as either TRUE or T and either FALSE or F, respectively, which are	Python throws an error for T and F, viz. "name 'T' is not defined". We need to use True and False (although without any quote signs)

S No	Purpose	R	Python
		recognized by R	and all-caps are not permitted (else, error: "name 'TRUE' is not defined")
10	Get the Type of an object	class(Vector_Name)	type(Tuple_Vector_Name) type(List_Vector_Name) # The < type() > syntax will tell us the type of the object, i.e. list or set or tuple or dict, etc # < Vector_Name.dtype > will work in dataframe where a single data type is present in each column, here for list or tuple < Vector_Name.dtype > will not be applicable
11	Data-type of variable in DataFrame	class(DF_Name$Var_Name) # viz. < class(DF_Name $Name) >	DF_Name.Var_Name.dtype , viz. < DF_Name.Age.dtype > DF_Name.Age.dtype
12	Get datatype of all variable of DataFrame	# Use str() function: str(DF_Name) # The result gives, the column/variable names, their attributes (i.e. numerical or Factor, etc), how many	# Use info() function: DF_Name.info() # The obtained result is similar to that of R. It gives all detail of the columns/variables. <class

S No	Purpose	R	Python
		observations/levels are there, and the initial values of each column. The obtained result is as followed: 'data.frame': 3 obs. of 3 variables: $ Name: Factor w/ 3 levels "AA", "BB", "CC": 1 2 3 $ Age : num 20 25 30 $ Ph.D. : logi TRUE FALSE TRUE	'pandas.core.frame.DataFrame'> RangeIndex: 3 entries, 0 to 2 Data columns (total 3 columns): # Column Non-Null Count Dtype --- ------ -------------- ----- 0 Name 3 non-null object 1 Age 3 non-null int64 2 Ph.D. 3 non-null bool dtypes: bool(1), int64(1), object(1) memory usage: 179.0+ bytes
13	Calling a Variable from a DataFrame	DF_Name$Var_Name viz. < DF_Name $Name >	DF_Name.Var_Name, viz. < DF_Name.Age > DF_Name['Var_Name'], viz. < DF_Name['Age'] >
14	Indexing from DataFrame	# Indexing starts from 1, i.e. the index of the first record is 1 # The from and to positions around a colon <:> symbol is meant according to the positional values, viz.	# Indexing starts from 0, i.e. the index of the first record is 0 # Row and column assignment is tricky. The from and to positions around a colon <:> symbol is translated as 1 less than

S No	Purpose	R	Python
		[2:8,3:5] means subsetting records starting from 2nd row to (and including) 8th row; as well as 3rd column to (and including) 5th column DF_Name[1,1] # Retrieve the first row, first column data-point DF_Name[2,2] # Retrieve the second row, second column data-point DF_Name[1,] # Retrieve the first row, all columns' data-points DF_Name[,1] # Retrieve all rows, first column data-points	the positional values, viz. [2:8,3:5] means subsetting records starting from 2nd row to (and including) 7th row; as well as 3rd column to (and including) 4th column Here, the start index for the row is 2, which refers to the 3rd row. Similarly, the column start index 3 refers to the 4th column. So just subtract 1 to get actually where it will be selected. DF_Name.iloc[0,0] # Retrieve the first row, first column data-point DF_Name.iloc[1,1] # Retrieve 2nd row, 2nd column data-point DF_Name.iloc[0,:] # Retrieve first row, all columns data-points DF_Name.iloc[:,0] # Retrieve all rows, first column data-points

S No	Purpose	R	Python
15	Subsetting a DataFrame	DF_Name[2:3,1:2] # Retrieve 2nd to 3rd rows, 1st to 2nd columns data-points	DF_Name.iloc[1:3,0:2] # Retrieve 2nd to 3rd rows, 1st to 2nd columns data-points # Note that in the last code, to refer to the last row we have put the index as last-row-number+1, although many rows are not there in the DataFrame. That means, the to position-index itself gets subtracted by 1
16	Extracting non-sequential records	DF_Name[c(1,3), c(1,3)] # To select 1st and 3rd Rows; as well as 1st and 3rd columns DF_Name[c(1,3),] # To select 1st and 3rd Rows; and all columns	DF_Name.iloc[[0,2], [0,2]] # To select 1st and 3rd Rows; as well as 1st and 3rd col DF_Name.iloc[[0,2], :] # To select 1st and 3rd Rows; and all columns
17	Extracting column(s) from DataFrame	DF_Name[, "Age"] # to extract all rows of the column "Age" # Single-column extraction will show the result in transposed layout DF_Name[, c("Name", "Age")]	DF_Name.loc[:, "Age"] # to extract all rows of the column "Age" # Single-column extraction will show the result in the original transposed layout, not in transposed layout DF_Name.loc[:, ["Name", "Age"]] # to extract all rows

S No	Purpose	R	Python
		# to extract all rows of the columns "Name" and "Age" DF_Name[, c("Age", "Name")] # Will just reverse the column order	of the columns "Name" and "Age" DF_Name.loc[:, ["Age", "Name"]] # Will just revrese the column order

18	Indicating a missing value in a DataFrame	# Use <Na> without quotes for missing value
		DF_Name_Miss_Val = data.frame(Name=c(NA, "BB", "CC"), Age= c(20, NA, 30), Ph.D.= c(T, FALSE, NA))
		
		# Note that the output varies between Character type columns (shows <NA> within <> delimiter) and numeric or Boolean type columns which print <NA> without the <> delimiter:
		Name Age Ph.D.
		1 <NA> 20 TRUE
		2 BB NA FALSE
		3 CC 30 NA
			# Use <None> without quotes for missing value
			import pandas as pd
			DF_Name_Miss_Val = pd.DataFrame({"Name" : [None, "BB", "CC"], "Age" : [20, None, 30], "Ph.D.": [True, False, None]})
			
			# The output gives <None>, without any delimiter and there is <None> for Character/string type and Boolean type columns, while <NaN> for Numeric type column
			Name Age Ph.D.
			0 None 20.0 True
			1 BB NaN False
			2 CC 30.0 None

S No	Purpose	R	Python
		# Note the difference between real NA (indicated by <NA>) and the string NA (indicated by NA) # The string appears as a level, the actual NA does not (c(NA, "NA")) factor(c(NA, "NA")) #[1] <NA> NA #Levels: NA	
19	Concatenate two 1-D objects	# Concatenating two variables/Objects # Both or all the 1D objects should be of the same data-type # Use concatenate operator <c()> to concatenate the 1D objects Obj1_Name <- c("AA", "BB", "CC"); Obj2_Name <- c("DD", "EE", "FF"); Conc_Obj <- c(Obj1_Name, Obj2_Name);	# Both or all the 1D objects should be of the same data-type # Just use <,> i.e. comma OR <+> sign between the 1D object names to concatenate the 1D objects Obj1_Name = "AA", "BB", "CC" Obj2_Name = "DD", "EE", "FF" Conc_Obj = Obj1_Name, Obj2_Name # Output: (('AA', 'BB', 'CC'), ('DD', 'EE', 'FF')) is a tuple within which two tuples are

S No	Purpose	R	Python
		Conc_Obj # Output: [1] "AA" "BB" "CC" "DD" "EE" "FF"	existing Conc_Obj = Obj1_Name + Obj2_Name # Output: ('AA', 'BB', 'CC', 'DD', 'EE', 'FF')

20	Concatenate two 2-D objects	# First split the data into two DataFrames: DF_Name1 <- DF_Name[1:2,];
		DF_Name2 <- DF_Name[2:3,];
		
		# Use rbind() function when both tables/DataFrames will have the same column names:
		DF_Name_Conc <- rbind(DF_Name1, DF_Name2)
			# First split the data into two DataFrames: DF_Name1 = DF_Name.iloc[0:2,];
			DF_Name2 = DF_Name.iloc[1:3,];
			
			# Use pd.concat() function when both tables/DataFrames will have the same column names:
			DF_Name_Conc = pd.concat([DF_Name1, DF_Name2], axis=0)
			
			# By default the parameter axis=0, which means it will concatenate by rows
			# axis=1 means concatenate by columns

S No	Purpose	R	Python
			DF_Name_Conc_Col = pd.concat([DF_Name1, DF_Name2], axis=1) # The result will show NaN where the column values are not matching in both tables

21	if-else condition	Marks <- 70
		{
		if(Marks < 60)
		{
		print('You have got 2nd Division')
		}
		else
		{print('Congrats!! You got 1st Division')
		}
		}
		
		# Even these lines of code (loc) could be written in a very dirty way, to save space and time:
		Marks <- 70 {if(Marks < 60){print('You have got 2nd Division')} else
			Marks = 70
			if Marks < 60: <Indentation>print('You have got 2nd Division')
			else:
			<Indentation>print('Congrats!! You got 1st Division')
			
			# The indentation, i.e. a Tab is a must in the execution statement line and the Python code is free from so many brackets and parentheses, however, the syntax is very strict.
			# Strictness of syntax: The indentation of <if> and <else> should be same; Thenext lines of execution following <if> and <else? conditions should have one more indentation,

S No	Purpose	R	Python
		{print('Congrats!! You got 1st Division')}}	mandatorily. Else, Python throws an error: <IndentationError: expected an indented block>

22	Multiple if-else conditions	Marks <- 70
		{
		if(Marks > 90)
		{
		print('Congrats!! You have got Excellent Grade')
		}
		
		else if(70<Marks & Marks<=90)
		{
		print('You have passed')
		}
		
		else
		{
		print('You have failed')
		}
		}
		
		# Don't use the else if condition as:
			Marks = 95
			if Marks > 90:
			<*Indentation*>print("Congrats!! You have got Excellent Grade")
			elif 70<Marks<=90:
			<*Indentation*>print('You have passed')
			else:
			<*Indentation*>print('You have failed')
			
			# The indentation, i.e. a Tab is a must in the execution statement line and the Python code is free from so many brackets
			# Here we can use the elif condition as 70<Marks<=90
			# Importantly, in Python <elif> is used instead of <else if>
			# Indentation and syntax

S No	Purpose	R	Python

		70<Marks<=90; It will throw error.
		# Again the lines of code (loc) could be written in a very dirty way, to save space and time:
		Marks <- 70
		{ if(Marks > 90){print('Congrats!! You have got Excellent Grade') } else if(70<Marks & Marks<=90){print('You have passed') } else {print('You have failed')}}
			are very strict in if-elif-else code

23	Creating Function: User-defined function	#Define a function for the quotient
		Quotient_Func <- function(x,y){
		print(x%/%y) # %/% operator returns the quotient (integer part of the result of division)
		print(x%%y) # %% returns the remainder
		}
		
		# Call the function:
			#Define a function for the quotient
			def Quotient_Func(x,y):
			<Indent>return x//y, x%y
			
			# Call the function:
			Quotient_Func(27,4)
			# Note that the <def> in Python is similar to <function()> in R
			# Besides, Colon symbol <:> is used in Python in stead of curly-brackets <{}>

S No	Purpose	R	Python
		Quotient_Func(27,4)	
24	Using System defined function	DF_Name = data.the frame(Name=c("AA", "BB", "CC"), Age= c(20, 25, 30), Ph.D.= c(TRUE, FALSE, T)) tolower(DF_Name$Name) # The general format is: Function_Name(DataFrame_Name$Col_Name)	import pandas as pd DF_Name = pd.DataFrame({"Name" : ["AA", "BB", "CC"], "Age" : [20, 25, 30], "Ph.D.": [True, False, True]}) DF_Name.Name.str.lower() # The general format is: DataFrame_Name.Col_Name.str.Function_Name() # The str() function converts the specified value into a string.
25	Reading a CSV file	DF_Name<-read.csv("~/Documents/Github/Homo_sapiens.GRCh38.85.gff3.gz", header = FALSE, sep = "\t", col.names = c('seqid', 'source', 'type', 'start', 'end', 'score', 'strand', 'phase', 'attributes'), comment.char = "#")	# Download the human genome annotation file from https://www.encodeproject.org/files/ENCFF783YZT/ : or type the following code: !wget ftp://ftp.ensembl.org/pub/release-85/gff3/homo_sapiens/Homo_sapiens.GRCh38.85.gff3.gz

S No	Purpose	R	Python
			# Open the *.gz gun-zipped file: DF_Name = pd.read_csv('Homo_sapiens.GRCh38.85.gff3.gz', compression = 'gzip', sep = '\t', comment = '#', low_memory = False, header = None, names = ['seqid', 'source', 'type', 'start', 'end', 'score', 'strand', 'phase', 'attributes'])
26	Import csv file	read.csv("File_Name.csv", header=T, sep="/t")	import pandas DF_Name = pandas.read_csv("1_Age_Wt_Ht.csv") DF_Name # pandas.read_csv("path//to//datafile//Datafile_Name.csv")
27	Save as csv file	write.csv(object_name, "File_Name.csv")	DF_Name.to_csv("Py_Test_Save.csv") # DF_Name.to_csv("path//to//directory//Datafile_Name.csv")

S No	Purpose	R	Python
28	Import xlsx file	install.packages("readxl"); library("readxl"); read_excel("Path where your Excel file is stored\\File Name.xlsx",sheet = "Your sheet name");	# Import Sheet 1 named 'dataframe' DF_Name = pandas.read_excel("R_Python_All_Example_Files.xlsx", 'dataframe') # pandas.read_excel("path//to//datafile//Datafile_Name.xlsx", 'sheet_name') # Import Sheet 2 named 'Stroke_Data_Kaggle' DF_Name_2 = pandas.read_excel("R_Python_All_Example_Files.xlsx", 'Stroke_Data_Kaggle') DF_Name_2
29	Save as xlsx file	install.packages("xlsx"); library("xlsx"); write.xlsx("Path where your Excel file is to be stored\\File Name.xlsx");	DF_Name_2.to_excel("Python_Test_Excel_Save.xlsx") # DF_Name.to_excel("path//to//directory//Datafile_Name.xlsx")
30	Show the head/tail of the DataFrame or	head(DF_Name) tail(DF_Name)	DF_Name_2.head() DF_Name_2.tail()

S No	Purpose	R	Python
	Table or Array		
31	Dimension of the dataframe	dim(DF_Name)	DF_Name.shape DF_Name.size DF_Name.ndim
32	Get the Unique entries in a particular column	unique(DF_Name$Col_Name) # To sort the output in descending manner sort(unique(DF_Name$Age), decreasing=T)	DF_Name.Age.unique() DF_Name['Age'].unique() #The generalized syntax is: # DF_Name.Col_Name.unique() # DF_Name['Col_Name'].unique()
33	Length of the 1D dataset	length(unique(DF_Name$Col_Name))	DF_Name.Name.unique().shape # DF_Name.Col_Name.unique().shape
34	Count the occurrence of each entry in a column of DF	table(DF_Name$Col_Name) sort(table(DF_Name$Col_Name), decreasing = TRUE) # Generate a dataframe of the table of counts of	DF_Name.Age.value_counts() # DF_Name.Col_Name.value_counts()

S No	Purpose	R	Python
		the entries: df_Ph.D. <- data.frame(sort(table(DF_Name$Ph.D.), decreasing = TRUE)) # Give column names of the dataframe df_Ph.D. colnames(df_Ph.D.) <- c("Is_Ph.D.", "Count") df_Ph.D.	
35	Select the rows containing a specific value in a particular column	DF_Name[DF_Name$Col_Name == "Entry_Name",] subset(DF_Name, Col_Name == "Entry_Name") # You can replace the entry name with the value	DF_Name[DF_Name.Name == 'Rat'] DF_Name[DF_Name.Age == 30] # DF_Name[DF_Name.Col_Name == 'Specific_Entry'] # DF_Name[DF_Name.Col_Name == Numerical_Value]
36	Get a random sample of size n of any object or a column of a DataFrame	sample(DF_Name$Col_name, 4) sample(1:100, 10)	DF_Name_2.sample(10)
37	Random number	rnorm(3, mean=10, sd=2); # Normal	import numpy as np # Generate random

S No	Purpose	R	Python
	generation (between 0 to 1) or other range	distribution runif(3, min=5, max=10); # define the range between 5 and 10 sample(1:100, 3, replace=TRUE); # Random integers	numbers of size 10 Random_Num = np.random.rand(10) Random_Num
38	Create a new column in the existing DataFrame	DF_Name$New_Col_Name <- log(DF_Name$Age)+DF_Name$Age	# First make a shallow copy and insert a new column that contains some calculations involving one or more columns: DF_Name = DF_Name.copy() # Import Numpy Library import numpy as np DF_Name['New_Col_Name'] = np.log2(DF_Name.Age) +DF_Name.Age DF_Name
39	The sum of a column	sum(DF_Name$Col_Name)	DF_Name.New_Col_Name.sum()
40	Performing a set of task	# For subsetting, we use the "isin()" function of Python, which corresponds to R's "%in%	# Suppose, we have created a new column 'Growth_Col' that contains values obatined by subtracting Col_Y from Col_X (i.e.

S No	Purpose	R	Python

		Selected_Farms = c("AA", "BB", "DD", 'M_Bar', 'M_Uni')
		
		# Which Names of DF_Name are present in Selected_Farms
		!DF_Name$Name %in% Selected_Farms
		
		# Subset the DF_Name DataFrame for the Names which are not present in Selected_Farms
		subset(DF_Name, !DF_Name$Name %in% Selected_Farms)
			Growth_Col= Col_Y - Col_X).
			
			# Now, we want to get the sum of the Growth_Col column for those animals whose Farm_Id's (maintained in Farm_Id_Col) matches "M_Bar" or "M_Uni" or code 1 to 3
			
			Selected_Farms = [str(_) for _ in range(1, 3)] + ["Rat", "Hat", "Ram", 'M_Bar', 'M_Uni']
			
			# Names that are common in both DF_Name & Selected_Farm
			Selected_Farms
			
			DF_Name[DF_Name.Name .isin(Selected_Farms)]
			
			# The names that are not present in Selected_farms: DF_Name[-DF_Name.Name.isin(Select

S No	Purpose	R	Python
			ed_Farms)] # Sum of the age column for the names that are not present in Selected_Farm DF_Name[-DF_Name.Name.isin(Selected_Farms)].Age.sum()
41	Select Chromosomes 1 to 29, X, Y, and Mitochondria from the Chrom_Col column	Chromosomes <- c(1:23, "X", "Y", "MT")	Chromosomes = [str(_) for _ in range(1, 23)] + ['X', 'Y', 'MT'] Chromosomes
42	Subset the dataframe to rows with the attribute “gene” in the “type” column, look at 10 random lines from the “attributes” column, and get the dataframe dimensions	ndf <- subset(edf, type == "gene") sample_n(ndf, 10)$attributes	ndf = edf[edf.type == 'gene'] ndf = ndf.copy() ndf.sample(10).attributes.values ndf.shape
43	Extract columns from DataFrame	# Not as Numpy array, but as an R-object:	import numpy col_Name =

S No	Purpose	R	Python
	as independent numpy array	dat0<- read.csv("1_Age_Wt_Ht.csv") dat_Ht<- dat0$Heigth_cm dat_Ht	numpy.array(DF_Name['Name']) col_Name
44	Change the column names	colnames(dat0)<- c("S_N", "Names", "Age_Mo", "Height", "Wt") head(dat0) # S_N Names Age_Mo Height Wt	DF_Name1 = DF_Name DF_Name1 DF_Name1.columns =['Col_1', 'Col_2', 'Age_Mo', 'Heigth_cm', 'Weight_', 'Log_Age'] DF_Name1
45	Change the row indexes	row.names(df_name) <- NULL	df=DF_Name.iloc[0:4, 0:2] df df.index = ['Row_1', 'Row_2', 'Row_3', 'Row_4']
46	Importance of strictness of syntax	R codes can be written flexibly, even just abiding by only the critical syntax	Python syntax (tab, same or next line, semicolon, etc) must be followed strictly
47	Assignment operator	# Either <- or = for Right operand to left operand assignment; # -> for Left operand to right operand assignment	# Only = operator for Right operand to left operand assignment; # There is no <- or -> operator for assignment purpose. # There is no Left operand

S No	Purpose	R	Python
			to right operand assignment operator (at least I have not got it) # < Left_Operand '+' '-' '*' '/' '**' '//' '%' = Value_to_work_on > will do sum, subtraction, multiply or division or exponential or quotient (i.e. division-result) or remainder on the Left_Operand with the Value specified on the right side to modify the Left_Operand. Example: X = 2, X += 5 results in X = 7; Similarly, X=3, X*=2 will modify X to 6

MATLAB

Several popular toolboxes are being used in MATLAB for AI-ML-DL-related analyses in veterinary and medical fields. Some of them are enlisted below:

Bioinformatics Toolbox

Database Toolbox

Deep Learning Toolbox

Deep Learning Toolbox

Medical Imaging Toolbox

Signal Processing Toolbox

Statistics and Machine Learning Toolbox

The cost of each of these toolboxes ranges between INR twenty-five thousand to one hundred thousand, which is quite affordable. The benefit of using the toolboxes are GUI based applications, almost all required results are provided and some modifications can also be made through a command-line-based approach.

Conclusion

The above chapter contains all the basic information required to start learning R and Python. The basic necessity is applying the skill and knowledge in the areas of research and study regularly. Programming languages are evolving daily. So one has to keep abreast with the changes in these languages.

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Chapter 5
Role of Smart Collars in Augmenting Animal Production

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Introduction

Artificial Intelligence can be a game-changer for the dairy farming in India and it can emerge as a tool that empowers farmers in monitoring, forecasting as well as optimizing the farm animal growth. It can predominantly change the scenario of dairy farmers by maintaining the health, physiological and physical conditions of dairy-cows. This knowledge-based technology has a huge potential and could confront the loopholes in dairy farming and thus indirectly can strengthen the dairy industry. In dairy farming AI has multiple applications like monitoring the activities of the dairy-cows, boosting the milk production and farm productivity, detection of mastitis in dairy-cows and developing the smart cow houses powered by image analysis. AI enables the dairy farmers to determine whether the cow is ill, ready to breed or has become less productive. The AI also sends alerts to the farmer about the change in the cow's behavior allowing human intervention where needed. Regular 24x7 monitoring of dairy animals is the key for successful dairy farming, however, traditional methods of monitoring relied on visual observation, but it was not very efficient due to the lack of time and human resources. Without AI, it would be almost impossible for the farmer to keep a watchful eye on every cow in the herd. Artificial Intelligence components of the dairy automation system process the collected data to provide insights on the heat stress, change in feeding efficiency and the estrus of the cow. Diseases like sub-clinical mastitis, one of the more common diseases in the dairy industry, cost the Indian dairy industry one billion dollars annually. Eventually, it provides new hope and open prospects for the overall quality and progress in the dairy industry through a profitable business approach in dairy farming.

Machine learning with data from GPS-enabled collars in dairy farming

Dairy farmers usually relies on workers to observe hundreds of dairy animals and dairy animals are notoriously stoic, often hiding symptoms of poor health from potential predators. GPS-enabled smart collars that are fitted to each dairy cow and coupled with an app that allows farmers to remotely shift virtually fence and proactively monitor their cow's health, feed, and behavior. The motion and temperature data of the livestock collected through the sensors are transmitted to a state-of-the-art gateway, this gateway is capable of collecting the sensor output from up to 250 neck collars transmitting simultaneously, ensuring minimal information loss in the transmission. The information received from all the collars is bifurcated and the gateway sends this information to the cloud for processing via cellular technology which is easily accessible in rural areas. The cloud is where different machine learning algorithms run to provide the health status of individual cattle through a live dashboard at the dairy farm (Smart Collar, IIT Ropar). The machine learned algorithms interpret the activity status of the cattle (chewing, ruminating, resting, moving) through the accelerometer sensor readings received and also monitor the heat cycle of the cattle based on the temperature and activity status. Inferences provided by the algorithms can be monitored live on the dashboard and based on the inferences, these algorithms also provide alerts to the farmers so that they can immediately know, for example, that the cattle need medical attention, or is going into the reproductive cycle. Heat alerts are important for timely insemination. This way, the status of each individual cattle can be monitored on the dashboard and the farmer just needs to do the needful whenever he receives an alert. This saves a lot of time and also allows efficient supervision of livestock well-being.

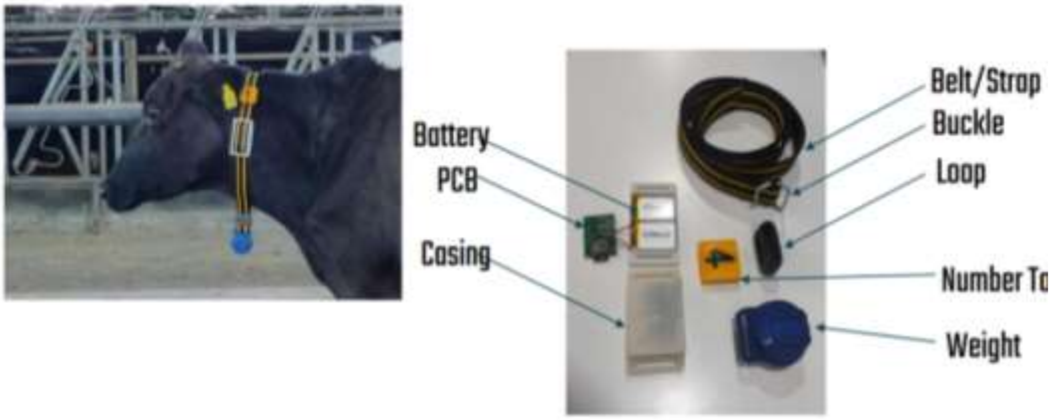


Fig 1: End node components of smart collar for dairy animals developed by IIT Ropar

In practice, these advanced technologies can be used to determine optimal solutions to many animal farming problems. A few examples include finding optimal solutions to minimize costs, maximize production, increase efficiencies, and create optimal diet formulations. Advanced models may even consider variables such as genetics, environment, and management priorities in order to come up with relevant and contextually optimal solutions. In general, the more diverse datasets a system collects and analyzes, the better are its chances of arriving at accurate and optimal solutions. Such a solution will also have the advantage of providing farmers an evidence-based or data driven solution.

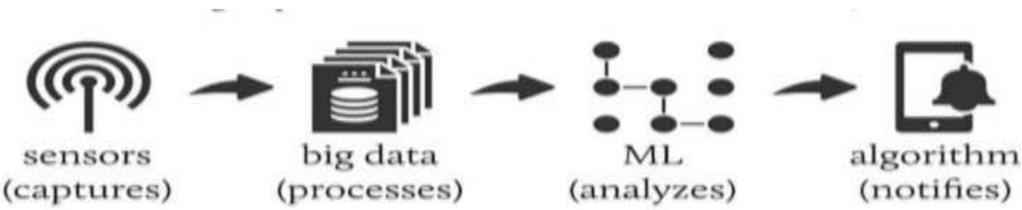
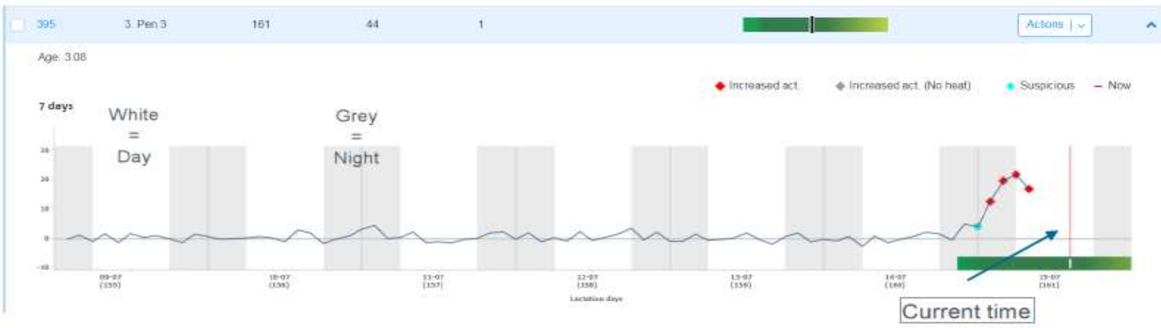


Fig 2: The collection of technologies, that we refer to as advanced technologies can help animal farmers create better outcomes

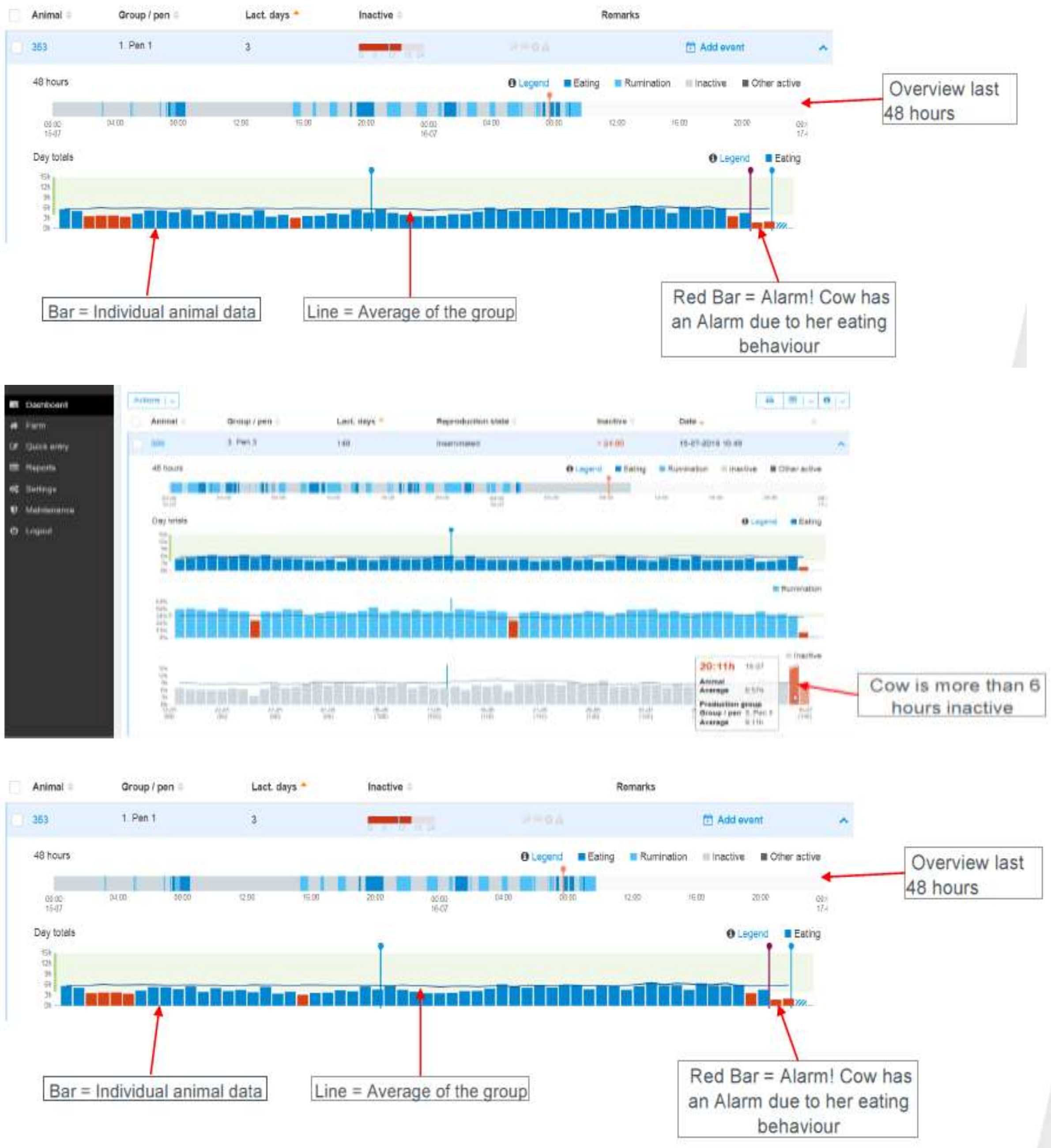
How to work with automated cattle health monitoring systems?

Data of the dairy animals through end nodes transmitted through gateway to the cloud for processing and interpretation of the data will be on the dashboard at the dairy farm.



- Individual animal observation

- Individual animal overview



Figures: Dashboard interpretation of data at Dairy farm

Emotional communication can be a useful tool to regulate social interactions such as mating competition, play, maternal nursing, and group defense. Harmonizing the emotional behaviors of individual animals can help other farm-animals develop more empathy and other desirable traits. This may result in the entire herd developing strong social bonds and improved group coordination.

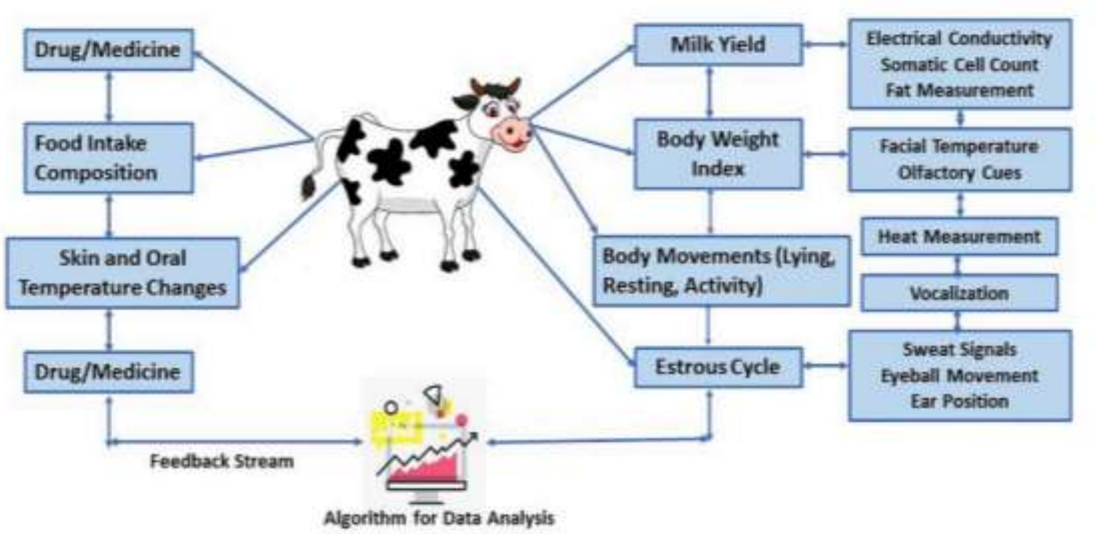


Figure 3: A representation of how machine learning algorithms might interpret data to create optimal growth conditions in dairy farming

Machine learned-based AI can help us identify the variables of emotional contagion based on vocalizations, olfactory cues, etc. to detect the outburst of a specific disease or stress (Figure 4). The animal farming industry is quickly becoming a hotspot for new technologies such as deep learning, AI, and ML. These smart farming technologies are being used to monitor animals, predict diseases, optimize food intake, and improve animal health.

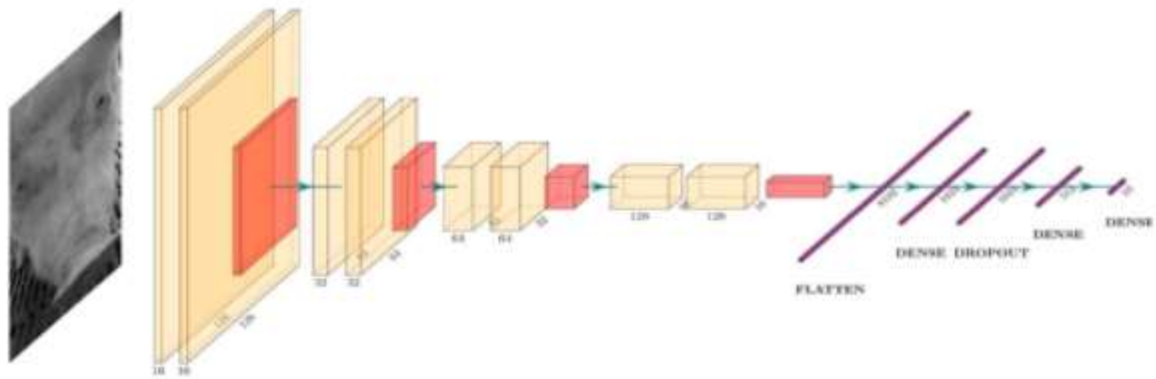


Figure 4: Flow diagram showing the neural network for emotional contagion of farm animals

Conclusion

Although Artificial Intelligence and Machine learning algorithms have developed so fast, there is a lack of standardization in the collection and sharing of data globally. However, as more farms get connected to technology, AI and sensing technologies will start playing a more decisive role in helping farmers see patterns and solutions to pressing problems in the modern livestock farming. Artificial Intelligence may improve the productive and reproductive parameters like milk yield, better conception rate, improvement in heat detection rate, lowers the incidence of disease. Eventually, it provides new hope and open prospects for the overall quality and progress in the dairy industry through a profitable business approach in dairy farming.

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Chapter 6
Artificial Neural Networks for Data Analysis

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Introduction

The global demand for meat and animal products is projected to increase by more than 70% in the coming decades (Neethirajan, 2020), driven by population growth and increased consumer purchasing power. Meeting this demand poses a significant challenge, as it requires producing more animals using limited land, water, and natural resources. To address this challenge, the agricultural industry is evolving and adopting new technologies.

State-of-the-art machine learning techniques, such as neural networks and decision trees, have the potential to revolutionize animal genetics and breeding. These data mining techniques can play a crucial role in breeding animals with high performance and resistance to biotic and abiotic stresses. The adoption of these technologies could lead to a major technological revolution in the field, enabling the integration of data-driven intelligent systems and cutting-edge digital fabrication technologies.

Technologies like the Internet of Things (IoT), big data analytics, artificial intelligence (AI), machine learning (ML), and blockchain have already transformed major industries (Akimana *et al.*, 2016). These technologies can also revolutionize the science of animal breeding, which heavily relies on data analysis. Their integration could pave the way for precision animal agriculture, enabling effective management, improved animal welfare, labor reduction, health surveillance, and reduced environmental impact (Hamadani, Ganai and Bashir, 2023). An advantage of adopting these technologies is that nearly half of the global population is already connected to the internet through smartphones or computers. Inexpensive mobile phones today have more computing power than the computers used in the Apollo 11 mission, making high computing power accessible to millions of farmers worldwide. This accessibility can facilitate the dissemination of new technologies to even the most remote areas.

Artificial intelligence can enable the mining of knowledge from large datasets, which would be challenging with conventional techniques. Following the revolution brought about by AI, it is believed that it has the potential to revolutionize agriculture and animal husbandry in every aspect. Intelligent systems provided by AI can enhance food production, improve processes, analyse real-time data from farm automation machinery, and promote animal welfare. AI techniques are making livestock farming easier and more cost-effective. This chapter provides an overview of data analysis using artificial neural networks which is one of the most popular machine learning technique.

Neural Networks

Neural networks, also known as artificial neural networks (ANNs), are a class of machine learning models inspired by the structure and functioning of the human brain. They are widely used for tasks such as pattern recognition, classification, regression, and decision-making.

At a high level, neural networks consist of interconnected nodes, called neurons, organized in layers (Khorshidi-Jalali *et al.*, 2019). These layers can be categorized into three main types:

Input Layer: The first layer of the network that receives the input data. Each neuron in this layer represents a feature or attribute of the input.

Hidden Layers: Intermediate layers between the input and output layers. They are responsible for processing and transforming the input data through a series of mathematical operations.

Output Layer: The final layer of the network that produces the desired output or predictions. The number of neurons in this layer depends on the nature of the problem being solved. For example, a binary classification task may have one neuron representing the probability of belonging to one class, while a multi-class classification problem may have multiple neurons representing the probabilities of different classes.

Neurons in a neural network are connected to neurons in adjacent layers through connections, which are represented by weights. Each connection has an associated weight that determines the strength or importance of the connection. The weights are adjusted during the training process to optimize the network's performance.

The information flow in a neural network is typically forward. It starts with feeding the input data into the input layer, which propagates the information through the hidden layers until reaching the output layer. Each neuron in the hidden layers applies a mathematical transformation to the input it receives, often involving an activation function. Activation functions introduce non-linearities to the network, enabling it to learn complex relationships between features.

The training of a neural network involves an iterative process called backpropagation, which updates the weights of the connections based on the difference between the predicted output and the actual output. This process aims to minimize a loss function, which quantifies the discrepancy between predicted and true values. Backpropagation calculates the gradients of the loss function with respect to the network's parameters and adjusts the weights accordingly, optimizing the network's ability to make accurate predictions.

Architectures

Neural networks can have various architectures depending on the specific problem and complexity of the data. Some common types of neural networks include:

Feedforward Neural Networks: These networks propagate information in one direction, from the input layer to the output layer. They are used for tasks such as classification and regression.

Convolutional Neural Networks (CNNs): CNNs are designed to process grid-like data, such as images (Bimantoro and Emanuel, 2021). They use convolutional layers to extract spatial patterns and hierarchical features.

Recurrent Neural Networks (RNNs): RNNs are well-suited for sequential data, such as time series or natural language processing. They have feedback connections that allow information to flow in loops, enabling them to capture temporal dependencies.

Long Short-Term Memory Networks (LSTMs): LSTMs are a specialized type of RNNs that can effectively capture long-term dependencies in sequential data by incorporating memory cells.

Neural networks have gained popularity due to their ability to automatically learn and extract intricate patterns from data. However, they require substantial amounts of labelled data for training and sufficient computational resources for complex models. Advances in deep learning, which refers to neural networks with multiple hidden layers, have significantly enhanced the capabilities of neural networks, leading to breakthroughs in areas such as computer vision, natural language processing, and speech recognition.

Data Analysis Using Neural Networks

While the process of data mining using AI is more or less the same, a quick overview of data analysis using neural networks is given below. Data preprocessing is an important part of preprocessing (Hamadani *et al.*, 2022).

1. Data Preprocessing:

Data Cleaning: Remove or correct any errors, outliers, or inconsistencies in the data.

Data Normalization: Scale the data to a common range to facilitate convergence during training. Common normalization techniques include min-max scaling and z-score normalization (Han *et al.*, 2021)

Handling Missing Values: Decide on an appropriate strategy to handle missing data, such as imputation or removal of incomplete records.

Feature Engineering: Transform and derive new features from the existing data to enhance the model's ability to capture relevant patterns and relationships.

2. Neural Network Architecture:

Input Layer: Represents the features or variables in the dataset. The number of neurons in this layer is determined by the dimensionality of the input data.

Hidden Layers: Comprise one or more layers between the input and output layers. Each layer consists of multiple neurons, and the number of neurons per layer is a design choice.

Activation Functions: Introduce non-linearities into the network, enabling it to learn complex patterns. Common activation functions include sigmoid, tanh, and ReLU.

Output Layer: Represents the desired output or predicted values. The number of neurons in this layer depends on the specific analysis task, such as binary classification, multi-class classification, or regression.

3. Training Process:

Loss Function: Defines the discrepancy between predicted and actual values. The choice of loss function depends on the nature of the problem. For example, mean squared error (MSE) is often used for regression tasks, while cross-entropy loss is suitable for classification problems.

Optimization Algorithm: Determines how the neural network's internal parameters (weights and biases) are adjusted during training to minimize the loss function. Gradient descent algorithms, such as stochastic gradient descent (SGD) and Adam, are commonly used.

Backpropagation: An algorithm used to compute the gradients of the loss function with respect to the network's parameters. These gradients guide the optimization algorithm in updating the weights and biases.

Batch Training: Instead of updating weights after each training example, training can be performed on mini-batches of data to improve efficiency and convergence.

Regularization: Techniques like L1 and L2 regularization or dropout can be applied to prevent overfitting, improve generalization, and control the complexity of the neural network (Van Rossum and Drake Jr, 1995).

4. Model Evaluation and Validation:

Train-Validation-Test Split: Divide the dataset into three parts: a training set used to train the model, a validation set to tune hyperparameters, and a test set to evaluate the final model's performance.

Evaluation Metrics: Choose appropriate metrics based on the analysis task. Accuracy, precision, recall, F1 score, mean squared error (MSE), and area under the curve (AUC) are common evaluation metrics.

Cross-Validation: If the dataset is limited, cross-validation can be employed to assess the model's performance by iteratively splitting the data into training and validation sets.

5. Hyperparameter Tuning:

Learning Rate: Determines the step size in the gradient descent optimization process.

Number of Hidden Layers and Neurons: The network's depth and width impact its capacity to learn complex patterns. Finding an optimal balance requires experimentation.

Regularization Strength: Hyperparameters like regularization coefficient control the impact of regularization techniques on the model's performance.

Batch Size: Determines the number of training examples processed before updating the weights and biases.

6. Deployment and Interpretation:

Once the model is trained and evaluated, it can be deployed to make predictions on new, unseen data.

Interpretability can be challenging with neural networks due to their complex nature. Techniques like feature importance analysis, activation visualization, and gradient-based attribution methods can aid in interpreting the model's decisions.

Software and Libraries

Several software and libraries are commonly used for data analysis using neural networks. Python, MATLAB and R, are popular languages for AI and a few important libraries are discussed below:

1. Python with Libraries (Van Rossum and Drake Jr, 1995):

TensorFlow: An open-source deep learning library developed by Google. It provides a comprehensive framework for building and training neural networks, including support for various types of networks and advanced features like distributed computing.

Keras: A high-level neural networks API written in Python. It is built on top of TensorFlow and offers a user-friendly interface for designing and training neural network models (Chollet and others, 2015).

PyTorch: Another widely used open-source deep learning library. It is known for its dynamic computation graph, making it suitable for tasks that involve complex control flow or dynamic structures.

scikit-learn: A versatile machine learning library that provides tools for data preprocessing, model selection, and evaluation. It includes basic neural network models like Multi-Layer Perceptron (MLP) and offers seamless integration with other data analysis techniques.

Pandas: A powerful data manipulation library that simplifies data preprocessing and feature engineering tasks. It provides convenient data structures and functions for handling structured data.

2. R with Packages (Bajaj, 2021):

Keras and TensorFlow: Similar to Python, Keras and TensorFlow are available in R as well. You can use them for building and training neural network models.

neuralnet: A popular package in R for training neural networks. It supports feedforward neural networks with customizable architectures and activation functions.

caret: A comprehensive package for machine learning in R. It includes neural network models, cross-validation techniques, and tools for hyperparameter tuning.

MXNet: A flexible and efficient deep learning framework available in R. It offers support for various neural network architectures and parallel computing.

3. MATLAB:

MATLAB provides a robust environment for data analysis and machine learning, including neural network modeling. The Neural Network Toolbox in MATLAB offers a wide range of tools and functions for designing, training, and evaluating neural networks.

Deep Learning Frameworks

Caffe: A deep learning framework specifically designed for speed and efficiency. It provides a command-line interface and a C++ library for neural network modeling.

Theano: A Python library that allows efficient mathematical computations, including deep learning tasks. It offers a flexible framework for constructing and training neural networks.

Microsoft Cognitive Toolkit (CNTK): A deep learning framework developed by Microsoft. It supports neural networks with efficient training algorithms and distributed computing capabilities.

PyTorch and TensorFlow, as mentioned earlier, can also be used with other programming languages like C++.

These software and libraries provide a wide range of functionality and flexibility for data analysis using neural networks. The choice depends on factors such as programming language preference, ease of use, specific requirements, and the level of community support available.

AI in Agriculture and Animal Husbandry

Artificial neural networks (ANNs) have the potential to revolutionize the fields of agriculture and animal husbandry by providing valuable insights, predictive models, and decision support systems. Here are some ways ANNs can be used in these domains:

- Crop Yield Prediction (Bajaj, 2021): ANNs can analyze historical data on crop yield, weather patterns, soil conditions, and agricultural practices to develop predictive models. These models can estimate future crop yields, helping farmers make informed decisions regarding planting strategies, resource allocation, and crop management.

- Disease and Pest Detection (Bradley *et al.*, 2019): ANNs can be trained on image data to identify and classify diseases, pests, and weeds affecting crops. By analyzing images of plant leaves or field scans, ANNs can help detect and diagnose plant diseases and pest infestations early on, enabling timely interventions and reducing crop losses.
- Irrigation Optimization: ANNs can analyze soil moisture data, weather forecasts, and plant characteristics to optimize irrigation schedules. By predicting water requirements accurately, ANNs help farmers optimize water usage, reduce water waste, and prevent over- or under-irrigation, leading to improved crop health and resource efficiency.
- Livestock Monitoring and Management: ANNs can analyze sensor data, such as temperature, humidity, and activity levels, from livestock farms. They can help monitor animal health, detect anomalies or distress signals, and provide insights for optimal animal management practices. ANNs can also predict livestock productivity, growth rates, and feed requirements (Hamadani and Ganai, 2022).
- Animal Disease Diagnosis: ANNs can assist in diagnosing animal diseases based on symptoms, laboratory test results, and historical data. By considering various factors and patterns, ANNs can provide veterinarians with decision support in identifying diseases accurately and recommending appropriate treatment strategies (Lloyd *et al.*, 2016).
- Feed Formulation and Nutritional Optimization (Carolan, 2020): ANNs can analyze nutritional requirements, ingredient characteristics, and livestock performance data to optimize feed formulations. By considering various parameters, ANNs can develop optimal feed compositions to ensure balanced nutrition, enhance animal growth, and minimize feed costs (Liebe and White, 2019).
- Market Analysis and Price Forecasting: ANNs can analyze market data, historical prices, supply and demand factors, and other relevant

variables to provide price forecasting models. This helps farmers and agricultural businesses make informed decisions about crop selection, production planning, and market timing.

- Smart Farming and Precision Agriculture: ANNs can integrate data from various sources, such as remote sensing, drones, and Internet of Things (IoT) devices, to enable precision agriculture practices. This includes tasks such as variable rate application of fertilizers and pesticides, site-specific farming recommendations, and automated decision-making based on real-time data.

Conclusion

ANNs are powerful tools which are being used the world over to bring about transformative changes. ANNs have the potential to improve productivity, efficiency, and sustainability in all spheres of life especially agriculture and animal husbandry. By leveraging the power of data analysis and machine learning, ANNs offer valuable tools for optimizing farming practices, reducing environmental impact, and ensuring better management of resources and livestock health.

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Chapter 7
Application of Artificial Intelligence in Clean Meat Production

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Introduction

A human-like intelligence that can learn to reason, plan, perceive, or analyze natural language is referred to as artificial intelligence (AI). It involves the theory and creation of computer systems that can carry out functions that would typically need human intelligence, like speech recognition, visual perception, decision-making, and language translation. The two AI algorithms that are most frequently employed are machine learning and deep learning. AI has the potential to revolutionize livestock sector through its various applications in addition to the one mentioned above like natural language processing, artificial neural networks, cloud computing, blockchain technology, internet of things, precision farming, sensor-based systems, robotics, so on and so forth. It is also said that AI will give birth to 'fourth industrial revolution' on the planet and it will be a digital revolution. These predictive models are employed by individuals, businesses, and governmental organizations and they learn data. There are so many ways by which AI can be used for farmers like development of learning simulations for the farmers who want to switch to livestock farming, deriving algorithms for ascertaining the animal production, deriving algorithms to understand the pattern and the amount of losses due to animal diseases and mortality, development of AI-Based Livestock Expert Systems, AI based meat production and processing systems, camera-based meat scoring systems, intelligent body scoring, etc. In the present chapter, we will focus on application of AI in meat production system to yield clean, hygienic and wholesome meat for consumers.

Meat consumption scaled by roughly 20% in the last ten years, according to the Organisation for Economic Cooperation and Development and Food and Agriculture Organization's (OECD-FAO) outlook report 2018-2027, and it is predicted to expand by 15% in the next ten years. The severe working conditions at abattoirs and meat plants, such as cold and wet operating rooms and long, laborious handling of large loads, all contribute to a skilled labour force shortage. This, combined with a significant growth in meat consumption, prepared the door for creative meat industry ways to handle this challenge, with robotisation and automation of meat plants being a crucial step. The employment of sensors, actuators, and software to accomplish specified tasks with varying degrees of autonomy is referred to as robotics.

Generic driving factors for automation in the meat industry	
Food safety	The introduction of microbial and foreign body contamination is significantly influenced by the human component. Overall production costs rise as a result of the high labour costs associated with maintaining sanitation in a typical meat processing facility.
Traceability	The option to gather traceability data (using automation programming) for quality control purposes may exist despite the fact that sensory data is innately needed for the automation of many processes.
Production quality	It is well-known that meat slices should be kept between 2 and 50 degrees Celsius. The quality of the cut increases as the temperature drops, but the need for greater cutting forces means that the worker's strength may not be sufficient to sustain the level of output quality. Automation allows for greater forces to be applied, maintaining or enhancing cutting quality and output rates.
Staff safety and welfare	Both trained personnel and less experienced workers sustain injuries, demonstrating that the danger lies more in the nature of the activity than in experience and that work is immediately stopped. Another issue is the expense of employer liability insurance.
Skilled labor	Due to the harsh working conditions, there is a shortage of competent labour for many of the duties in the slaughtering and meat processing industries.

Motives for automating operations and using robotics

Automation is used to improve productivity, safety, efficiency of processes, and product quality. Typically, a control system that has been "programmed" with a set of instructions is used to accomplish this. The following are the justifications for industrial process automation:

- Boost the rate of both qualitative and quantitative productivity.
- Tough to do the task manually
- It is challenging to constantly meet requirements
- Developments in automatic stunning, deboning, and line speed.
- Automation speeds up primary processing in a more effective way.
- Robotics and automation allow for process flexibility.
- Quality assurance
- Potentially dangerous to workers
- Cut down on pandemics and other diseases brought on by human contact
- Bacterial and microbiological contamination is decreased
- Meat quality is improved

Novel Methods for Ascertaining Meat Quality

Meat quality is a very complex term and it comprises various aspects which can differ according to the user's standpoint i.e., different factors or properties are important for producer, meat processor or consumer. From the animal production perspective, the quality mainly refers to lean meat content on which the payment to the farmer is based. Processing industry on the other hand is interested in meat technological quality (suitability for further processing) and factors affecting consumer's choice. The consumer is sensitive about meat appearance (colour, lean to fat ratio), its sensory quality, nutritional value (macro and micro nutrients) and safety (presence/absence of toxic compounds, drugs, and pathogen or spoilage micro flora). Other factors like the way meat is produced (animal welfare, ecology) can also affect consumer's choice. In meat production and processing, different properties can play an important role in quality classification of meat for different purposes or can be critically appraised by consumers (often their basis for meat selection or rejection). In pork for example, water-holding capacity of meat has big significance, whereas in beef, tenderness is an important attribute. Spoilage detection or meat shelf-life is also an important issue in meat sector. In the last decades, the methods used in meat evaluation, meat quality control, or inspection have undergone important developments with the application of novel technologies like computer (machine) vision, spectral imaging, spectroscopy, electronic nose or bio-sensing technologies. As far as AI is concerned, it is catching the attention of businesses across many disciplines and sectors with Food Processing and Handling (FP&H) being one of them.

Major Applications of AI in Meat Production & Processing

However, AI is used at an increasing rate in food industry but for meat sector, the application can be categorized into following types:

- Meat Sorting
- Meat Packaging
- Food Safety Compliance
- Maintaining Cleanliness
- Developing Products
- Helping Customers with Decision Making

Application of Industry Robotic Technologies to Meat Processing and Preservation

The requirement for sustainable food systems necessitates the development of novel strategies to secure the global food supply while minimizing food losses and waste across the supply chain. The employment of robotic technology in the processing chain and during meat preservation is especially important in this case since it might avoid food waste. Robotics and automation systems are among the techniques that could assist reduction in waste and maintain enough production because they support speedy processing by minimizing sources of contamination and thus improving the shelf life of the meat. However, due to the uniqueness of animal carcasses and the locations derived from them, robotization and automation procedures provide a challenge for Meat. In spite this initial difficulty, the development and application of robotization and automation are of particular interest because the secondary processing of the carcasses and the tasks associated with slaughter are currently labors that require the majority of manual work, which is repetitive and must be done quickly. Even though it is true that many processing procedures in slaughterhouses (such as stunning, bleeding, scalding, plucking, skinning, evisceration, splitting, and cooling) are already effectively automated, hardware and software still need to be developed in order for robots to provide a flexible, scalable, compact, and profitable alternative in the production line when it comes to the secondary processing of meat. Because cutting and boning involve skill and knowledge throughout processing, they are among the most labor-intensive activities. In the main and secondary stages of meat processing, there are some automated systems that use detection units based on vision scanners to determine the path and depth of the meat cuts. The use of laser lines that enable 3D scanning in automation for cutting is popular in this regard. The Frontmatec Company's AiRA Robotics system, created for use in the clean line of pig slaughterhouses, is a fairly well-known example of automation in the meat business. The robot and saw combination, the robot and knife combination, and even a pair of robotic arms are all included in Frontmatec's technology. Various IR 4.0 technologies are currently available for the deboning (removal of the femur and tibia) of the rear legs of pigs using robotic systems.

Application of a vision system that is capable of extracting data to count ribs and identify the dorsal spine, as well as a robotic arm that performs the necessary cut is a revolutionary progress. The "eye-to-hand" vision system comprises of a camera and a projector that execute a 3D triangulation reconstruction in order to count and identify the dorsal spine and the ribs, respectively. The hindquarters and forequarters are then taken after the cutting route has been defined. Given that chicken has less variances in carcasses than other larger animals, the companies that process this meat are currently the most automated in the meat industry. However, the initial processing of poultry involves automation. Due to this reality and the strong demand for chicken meat, the industry is continuously in need of intelligent technologies that will enable it to boost industry yield, particularly during the secondary processing of poultry (cutting and boning). Some effective systems have been created in this regard, such as GRIBBOT, a robot for harvesting chicken fillets that consists of a 3D vision subsystem for the acquisition of RGB-D images, a specially built gripper, and a carrier system to expose the breasts to the robotic arm. The robotic mechanised harvesting of front half chicken fillets using GRIBBOT is a wholly new concept. Commercial automation of this process will not only boost the poultry industry's production capacity and profitability, but it may also make it possible to use more raw materials earlier in the production process.

The gold standard for accurately identifying the lean and fat components of carcasses is computed tomography (CT), which has been utilised extensively. One of the most extensively studied non-destructive, non-invasive approaches for assessing corpses is video image analysis (VIA). The first generation of VIA technology measured Hot Standard Carcass Weight (HSCW) by taking 2D photos of the sides or carcasses. In order to estimate yield, conformation, and EUROP fat and conformation scores, colour (red, blue, and green scale) and dimensional data are retrieved from these images. In more current VIA systems, full 3D reconstructions are produced using striping or structured light. According to the scientific literature, the complete beef body VIA technology is helpful for determining the composition of the beef carcass. However, the present tendency opposes the continuation of systems based on hard work performed by operators with the goal of improving job quality and minimising pathologies linked with it (musculoskeletal illnesses). As a result, technologies that integrate human-robot collaboration are being studied, with the goal of developing CoBots, which would be a highly beneficial tool in the meat sector. Furthermore, the usage of CoBots would facilitate the inclusion of newly arrived operators by allowing them to receive a step-by-step approach to processing, thereby completing their training.

Introduction of sensors in the food Industry throughout the entire process enables the meat factory to include rapid, real-time, and continuous parameter control. Similarly, sensors could enable the control of meat characteristics related to production and the sustainability of its processing because, for example, when a meat defect is identified in real time in the production chain, action could be taken to obtain the appropriate product, which would otherwise reach the supermarket shelves and be rejected by the consumer (favouring food waste). The use of smart sensors, which can be incorporated into smart packaging materials in the form of films, labels, or barcodes to provide information on changes in time and temperature, pH, humidity, gas levels, chemical composition, microbial contamination, etc., can be highlighted in the case of the preservation of meat products. These sensors can be seen being used to detect meat in smart packaging as part of films. These films, which integrate the sensor into their matrix (often made from a natural substance, such as anthocyanins, curcumin, etc.), are typically made from natural polymers such proteins and carbohydrates. As a result, this innovative technology has made it possible to keep track of the freshness of meats including chicken, hog, cattle, and lamb. The sensors' ability to spot even minute or subtle changes in meat during storage could improve how well it is preserved. IoT and blockchain technologies, which are similar to sensors in that they assist maintain results transparency, become crucial tools to regulate the monitored results.

Automation in the pork processing industry

Automation has been most successful in the pork meat processing business, which shares parallels with the red meat industry. RoBUTCHER is an experimental project financed by the European Union to build autonomous robotic cells known as meat factory cells (MFC). It is a concept that uses cells to replace traditional linear production techniques. In most abattoirs, the procedure begins with slaughter, then moves on to dehairing, evisceration, splitting the carcass into halves, and ultimately deconstructing each half into primary and secondary cuts after cooling. However, the MFC concept proposes rearranging some duties so that the carcasses are delivered straight to the autonomous cells after dehairing for hot boning of the primals, followed by internal organ removal.

This system consists of two robotic arms, one for manipulation and gripping and the other for cutting. During the procedure, the carcass handling unit (CHU) supports and retains the carcass. The system can adjust to differences between carcasses by combining detailed computed tomography (CT) data, real-time 3D imaging, and human-expert cutting data for neural network training towards cutting trajectory planning. An RGB-D camera's visual data tries to detect the carcass's sections and important properties, which is then fed into a machine-learning algorithm to calculate the ideal gripping site and cutting trajectories. Frontmatec, one of the largest meat processing automation firms, has successfully developed a number of automated systems for pig cutting, fat removal, and trimming e.g. AGOL-800, AMBL 1100 etc. Another technology made to execute extremely exact trimming of pork belly, focusing on the teat and backside parts, is the robotic belly trimmer. To construct a 3D model, the technology uses a vision system and information from over 300,000 measurements. This model is then used to identify the contour of the belly. The trimming operation is subsequently carried out by the system using two 6-axis robots, one of which is outfitted with a water jet cutter. For the deboning of pork shoulder and leg, the Mayekaya firm introduced the commercially available systems HAMDAS-RX and WANDAS-RX. The systems use X-ray vision to locate the connective tissue to be sliced before separating the muscles from the bone. To help the knife follow the surface of the bone, these systems also offer a feature.

Automation in the beef processing industry

In the abattoir for processing beef, very few activities have been automated. Scott Automation created an automated robotic system for rib scribing. It slices the rib in two straight lines using a circular saw that is mounted on the end of a manipulator. In order to determine the cutting path with respect to the bone's structure, a combination of X-ray (DEXA) and a colour camera is used. By using force and vision to execute the Z cut, which requires less manipulation when quartering a cow carcass. Using a structured light source and a camera, the system determined the carcass' topography. The details of the carcass were caught by the camera using the light as their source.

Robotic Hide Puller

Robotic hide puller is a new addition to meat industry which is based on the principle of automation, artificial intelligence and reduction of human touch. This machine as the name suggests, is used to remove hides from the body of slaughtered animals in a downward pulling motion. It pulls the hide from the tail area down along the back and finally over the head. The main operations of the machine are controlled using metered hydraulic pedals. It reduces the human touch and enhance the quality of meat. The principle of clean meat production can be actuated using automatic hide puller. The machine is made up of rust-resistant GI steel. Further, the motion cameras and intelligent cameras analyse the quality of meat and ensure safe consumption.

E-Nose or E-Tongue

Electronic nose or electronic tongue is also known as electronic sensing or e-sensing. It is a complex array of sensors which are linked to create a detection system for taste, odour and flavours. An e-nose or e-tongue is combination of gas sensors or chemical sensors which mimics human nose or human tongue. Depending on the sensing materials, gas sensors can be classified into several types including, conducting polymers (CP), metal-oxide semiconductor (MOS), quartz crystal microbalance (QCM), and surface acoustic wave (SAW) sensors. The chemical sensors commonly employed for an e-tongue include electrochemical sensors, biosensors, and optical mass sensors.Typically, rapid sensing can be achieved by those sensor arrays, and the price of a sensor array is relatively lower than the standard analytical equipment, such as gas chromatography–mass spectrometry (GC–MS), laser scatting analyzer, and high-performance liquid chromatography (HPLC). Sensor arrays have broad applications in determining food quality-related properties, such as sensory attributes, microbiological properties, and processing quality. The data collected after using these sensors can be analysed for ascertaining meat quality through artificial neural networks.

AI based techniques for detection of adulteration in meat

In recent years, artificial intelligence has been extensively employed to combat meat adulteration. Using AI to identify meat adulteration entails training algorithms by maintaining data sets of real and counterfeit items in order to detect minute compositional variations. These changes are then used to construct models that can precisely assess whether or not meat has been tampered with by sensing distinct meat. This technology has a high potential for detecting adulteration that is not detectable by human examination or traditional laboratory approaches. Artificial neural networks (ANN), deep learning (DL), fuzzy logic (FL), support vector machines (SVM), and random forest (RF) are some of the AI techniques that can quickly assess the qualities of meat.

CNN has advanced to the highest level of image pattern recognition. CNN has been demonstrated to be one of the most important methods for learning deep characteristics of input digital information in classification and regression applications. CNN networks differ from traditional neural networks in that CNN use a sequence of convolutional layers. The convolutional layers' goal is to extract high-level characteristics from an input image.

For quick and non-destructive minced meat identification, Vis-NIR spectroscopy has been integrated with AI. Fortunately, thanks to numerous artificial intelligence methodologies and technical breakthroughs, it is now possible to identify the type of red meat by simply taking a picture of it at the food market. A fine-tuned ViT model was utilised to distinguish between beef, horse, and pork. The classifier passed the assessment with 97% accuracy. A model that can distinguish between different forms of red meat. It also intends to evaluate the performance of cutting-edge CNN in computer vision with the transformer architecture. A small dataset from an internet repository was gathered for this purpose. RGB photos of beef, horse, and pork meats are included in the dataset.

Production of Minced Meat Using Process Control Computer (PCC)

Modern trends in the development of meat processing equipment include the use of highly precise methods for meat raw material analysis and high-calibre control of raw meat processing. In the traditional technology for minced meat production, using batch-operated technological units, finished product quality, to a large extent, depends on the operator. The new technology, realised on the proposed automatic line, envisages complete automation of the technological process with the use of the PCC which is an Intelligent Control System (ICS); that is, control is conducted according to the principle of an unmanned operation based on artificial intelligence (Figure 1). This will allow finished products of guaranteed high quality to be obtained by computer control both of each technological operation and the whole technological process in realtime.

Near Infra-Red Spectroscopy for Meat Freshness

Increasing concerns about adulterated meat encouraged industry looking for new non-invasive methods for rapid accurate meat quality assessment. Main meat chromophores (myoglobin, oxy-myoglobin, fat, water, collagen) are characterized by close comparable absorption in visible to near-infrared (NIR) spectral region. Therefore, structural and compositional variations in meat may lead to relative differences in the absorption of light. Utilizing typical fiber-optic probes and integrating sphere, the degradation of meat samples freshness can be observed at room temperature referring to the relative changes in absorbance of main meat chromophores. The data obtained after NIRS can be subjected to principal component analysis (PCA) for obtaining the stage of freshness which is not observed by the conventional analysis of the reflectance spectra. This approach is highly precise for assessing meat quality and monitoring relative absorbance alternation of oxymyoglobin and myoglobin in visible, and fat, water, collagen in NIR spectral ranges. As far as PCA is concerned, PCA is an advanced analysis technique for reducing the dimensionality of datasets which increase interpretability but at the same time minimizing information loss. It does so by creating new uncorrelated variables that successively maximize variance.

Meat Quality Evaluation using Computer Vision

Imaging technique or computer vision (CV) technology has received huge attention as a rapid and non-destructive technique throughout the world for measuring quality attributes of agricultural products including meat and meat products. Computer vision is concerned with the theory behind artificial systems that extract information from images. The image data can take many forms, such as video sequences, views from multiple cameras, or multi-dimensional data from a medical scanner. The application of computer vision in the industry, where information is extracted for the purpose of supporting a manufacturing process, is called machine vision. Like ultrasonography provides the reflection signature about the inner structure of the medium, similarly computer vision provides details about the meat structure. Classical methods of meat quality assessment, however, have some disadvantages like they are expensive and time-consuming, whereas CV has several advantages over the traditional methods. It is non-destructive, easy, and quick, hence, more efficient in meat quality assessments. In CV, spectral imaging or spectral analysis is done based on the principle component of meat color i.e. myoglobin. The CV presents the color simulation results of meat samples based on data on the content of various forms of myoglobin in different proportions after subsequent analysis. Even pictures taken from a simple camera can be analysed for ascertaining meat quality. After standardization and calibration of CV for meat quality, the prediction accuracy can be increased for meat color, pH, DL, crude protein and ash content of the sample.

Spoilage Identification/Storage Time Assessment

Meat and meat products are highly susceptible to spoilage or contamination, affecting the quality and safety of the products. Many of the methods used for the detection of spoiled or contaminated meat are based on immunological or nucleic acid based procedures which are time consuming, laborious and demand trained personnel. At present no method is available for a real-time, non-destructive, reagentless, quantitative and relatively inexpensive monitoring. According to Ellis & Goodacre (2001) interesting analytical approaches include biosensors, electronic noses, infrared spectroscopy upgraded with machine learning methods like ANN, CNN, etc.

Bio-sensing technology

The meat industry associated with the health hazards like deadly pathogens, veterinary drugs, pesticide residues, toxins and heavy metals is in need of a tool to tackle the awful situation and ensure safer product to consumer. The growth in the industry, global trade scenario, stringent laws and consumer awareness has placed an extra onus on the meat industry to meet out the expectations and demands. Biosensors are the latest tool of detection in the fast-growing industries including the food industry. Biosensors can be defined as an analytical device, which converts a biological response into an electrical signal and consists of two main components: a bioreceptor or biorecognition element, which recognizes the target analyte and a transducer, which converts the recognition event into a measurable electrical signal (Velusamy et al. 2010). Bio-sensing technology combines a sensitive biological element (e.g. enzymes, microorganisms, antibodies, *etc*.) with a physicochemical detector of an analyte (optical, piezoelectric, and electrochemical). The physicochemical detector transforms the interaction of the analyte with the biological element into a signal which can be measured and quantified. The results are displayed in a user-friendly way. Biosensors are rapid method of meat quality assessment and can be used for bulk meat testing.

Application of ANN for carcass quality or classification

The meat business is looking for lean and conformed carcasses with high meat outputs. The so-called carcass grading or classification (used for pig, bovine and lamb carcasses) is completed at the conclusion of the slaughter line and serves as the foundation for payment to the farmer. Another example is in poultry, where carcasses are evaluated for wholesomeness at the slaughter line and those with an abnormal appearance (tumorous, bruised, skin-torn, septicemic, corpse, air-sacculitis) are eliminated. The aforementioned approaches are primarily reliant on visual evaluation and hence vulnerable to human limitations (speed, error, fatigue). ANN can be effectively used to ensure carcass quality at the slaughterhouses.

Intelligent Cleaning Systems

Maintaining cleanliness is a massive concern in meat handling and production factories, slaughter houses, abattoirs, butcheries, etc. Customers have also become intelligent, and they know that having every process automated does not mean the product will be safe to eat. According to the University of Nottingham, equipment cleaning accounts for almost 30 per cent of energy and water supplies of a food processing plant. They claim that their AI-based sensor technology is capable of saving nearly $133 million per year and also save time (by 50%), energy, and water to clean the equipment. Traditional cleaning systems did not include any sensors which resulted in residual of meat particle in vessels of equipment. The system was unable to clean small food particles which the new self-optimizing cleaning system could. It uses optical fluorescence imaging and ultrasonic sensing technologies to deliver data to the machine learning algorithm, which will help to monitor the microbial debris and food particles in the equipment.

Conclusion

Despite being at its initial stage, AI is reshaping the meat production and processing handling business. In upcoming years, it is going to revolutionize the meat sector forever. Today, development continues along traditional lines, but advances in artificial intelligence and robotics are expanding the capabilities of manufacturing methods. Researchers might concentrate on various methodologies such as the meat factory cell. Instead of delegating a specific task to a robotic arm, this may carry out a variety of operations on the carcass. The creation of such systems may be appealing to smaller producers who cannot afford to spend much in automation, but they may also be scalable to larger producers when applied in parallel. AI will help meat-based companies to increase their revenue by speeding up the production process, reducing maintenance time and hence the production downtime, decreasing the chances of failure by automating almost every process and eventually delivering an excellent customer experience by predicting their likes, dislikes, and desires. It will further add-on to enable fewer human errors and less waste of abundant products; lowering costs for storage/delivery and transportation; and creating happier customers.

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Chapter 8
Blockchain Applications in Animal Production, Health and Marketing

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Introduction

Blockchain technology, with its decentralized and immutable nature, has the potential to revolutionize various industries, including livestock production, health, and marketing. The livestock industry plays a crucial role in the global economy, providing food, employment, and livelihoods for millions of people worldwide. However, the industry has faced challenges related to transparency, traceability, and trust in various stages of the supply chain. Blockchain technology is a decentralized, transparent, and secure digital ledger that has the potential to transform the livestock sector by addressing these challenges. In this chapter, we will explore how blockchain can enhance transparency, traceability, and trust within the livestock industry. We will delve into its applications in livestock production, health management, and marketing, highlighting the benefits it offers to stakeholders across the supply chain.

Blockchain Basics

A blockchain is a decentralized or distributed, transparent, immutable, and democratic encrypted transactions ledger, where each transaction creates a node. These nodes are organized into records, known as “blocks”, based on consensus from participating parties (peers), and blocks are linked, with unique hash codes, to form a chain. Each time there is a new transaction, another node is created in real time with information about that transaction to contribute to the blockchain. To understand this, we can take example of money transfer between two individuals in which there is involvement of many stakeholders viz. two individuals, banks, payment gateways, transferring agencies, etc. which leads to time delay and cost. However, the same is eased by the use of blockchain technology and the transactions are recorded in real time with proper timestamping.

The Beginning of Blockchain

Satoshi Nakamoto is the name used by the presumed pseudonymous person or persons who developed bitcoin in 2008, which led to the beginning of bitcoin blockchain. Bitcoin is the currency or the incentive which is paid to the miners who do data mining and maintain blockchain. Blockchain is a distributed network and no one owns it. The major applications of blockchain technology in livestock sector is detailed below.

Supply Chain Transparency

Blockchain technology has the power to revolutionize supply chain management in the livestock industry. By recording transactions and data in an immutable and transparent manner, blockchain enables stakeholders to track the entire journey of livestock, from birth to the consumer's plate. Each transaction, such as breeding, feeding, vaccinations, and transportation, can be recorded on the blockchain, providing an auditable and tamper-proof record. From breeding and feeding to transportation and processing, all relevant information, such as breeding history, vaccination records, and feed sources, can be securely stored on the blockchain. Blockchain enables real-time visibility and transparency in livestock production by recording and storing data at every stage of the supply chain. This transparency fosters trust among consumers and allows them to make informed choices about the products they purchase. The consumers can verify the origin, quality, and ethical standards of the livestock products they consume.

Provenance and Authentication

With blockchain, the provenance of livestock products can be easily established. By recording information about the animal's origin, breed, age, and health records on the blockchain, consumers can verify the authenticity of the products they buy. This feature is particularly crucial in combating food adulteration and ensuring food safety.

RFID Tags and Unique Identification of Animals

The unique ID remain with that animal throughout its existence, to collect data on: the farm(s) it has lived in, the transportation used to convey the animal from the farm(s) to the slaughterhouse, the veterinarian checking the animal at the slaughterhouse, the quality check following slaughter, the transport of the meat product, finally details of the packager and retailer, which ensures complete safety of food reaching the table of the consumer.

Secure and Immutable Health Records

Blockchain technology facilitates the seamless recording and sharing of information related to animal health and welfare. Veterinary records, including vaccination history, disease outbreaks, and treatment protocols, can be stored on the blockchain. This enables real-time monitoring of livestock health and ensures compliance with regulatory standards. In the event of a disease outbreak or contamination, the blockchain can facilitate rapid identification, containment, and recall of affected products, thus minimizing the risk to public health.

Traceability of Medication and Feed

Ensuring the safety and quality of medication and feed is paramount in livestock health management. Blockchain can be used to track the entire supply chain of veterinary medicines and animal feed, from production to distribution. This ensures that only approved and safe products are used, reducing the risk of contamination or illegal substances entering the food chain.

Enhanced Product Labelling and Certifications

Blockchain enables the creation of digital product labels that provide comprehensive information about the livestock products. This includes details such as breed, rearing conditions, feed sources, and animal welfare standards. Certifications, such as organic or free-range, can also be securely recorded on the blockchain, allowing consumers to verify the authenticity of claims made by producers.

Smart Contracts and Payments

Blockchain technology can streamline financial transactions in livestock production and marketing. Smart contracts, self-executing agreements written in code, can automate processes such as payments, contracts, and settlements. Farmers, suppliers, processors, and retailers can engage in secure and efficient transactions, eliminating the need for intermediaries and reducing transaction costs. Additionally, blockchain-based payment systems can enable immediate and transparent settlements, ensuring timely compensation for livestock farmers and enhancing their financial stability.

Building Consumer Trust and Empowering Ethical Consumption

Consumers are increasingly demanding transparency and ethical practices in the livestock industry. Blockchain technology can empower consumers to make informed choices by providing access to a wealth of information. By scanning a product's QR code, consumers can access data on the animal's breed, feed, living conditions, and sustainability practices. This transparency encourages ethical consumption, rewards responsible producers, and fosters trust between consumers and the livestock industry.

Promoting Sustainability and Environmental Stewardship

Blockchain technology can also play a vital role in promoting sustainability and environmental stewardship in the livestock sector. By recording and verifying data on the blockchain, stakeholders can track the environmental impact of livestock production, such as carbon emissions, water usage, and land management practices. This data-driven approach allows for the implementation of targeted strategies to reduce the industry's ecological footprint and incentivize sustainable practices.

Weather Prediction for Forage Production

Weather and climate extremes impact forage conditions and lead to loss of animal production and livelihood of pastoralist communities. Monitoring of forage conditions and developing a reliable early warning system can reduce the loss of livestock and improve the resilience.

Vaccine and Medicine Production

Analyzing and securing animal health safety by sourcing and using quality materials, managing supply chains, traceability and record keeping of ingredients, compliance with required standards for production, storage, and transport of vaccines/medicines.

Detecting and Tracking Diseases

H1N1 swine flu, Foot-and-Mouth and Mad Cow diseases in Europe, Avian influenza, and recent increases in salmonella outbreaks can be tracked and detected. In the event of a livestock disease outbreak, farmers can input and access disease data, actively helping to control the outbreak or prepare other farmers for an outbreak.

Tracing Livestock Based Harmful Foods

According to the World Health Organization, 1 in 10 people experience food-related illness every year, with over 420,000 people dying annually. Blockchain technology could help trace harmful foods back to the source, increasing traceability and accountability for problematic practices within livestock.

Livestock Based Food Traceability

Australian meat production project, “paddock to plate” tracks beef along the “farm to fork” chain. Consumers can use their smart phones to scan the QR code to get information about the animals involved, their feed and overall nutrition, slaughter and packaging dates, and meat safety test results. The Gogochicken company fixes an ankle bracelet to monitor the movements of chickens and their behavior via GPS tracking. This information is provided to the customers through the web to guarantee them that the chickens are actually free range.

Livestock Feed Safety

The feed chain is highly multi-actor, comprising of millers, transporters, wholesalers, distributors, retailers, and farmers, and these are physically widely distributed. Till date, this system is inefficient and unreliable and lacks transparency and traceability. The cost of operating such a supply chain is also high and is vulnerable to fraud. A well-designed blockchain because of its transparency and immutability prevents tampering to strengthen feed-food nexus. Inappropriate addition of growth promoters, antibiotics and other chemicals can also be alleviated.

Management of Livestock Waste

A case study was conducted in China on the application of blockchain technology in incentivizing efficient use of rural wastes. A digital coupon or cryptocurrency to trade the wastes among the farmers and entrepreneurs was formulated. The trucks connected to blockchain lifted the wastes and transported it to energy generation plants. Farmers received payment based on the waste and energy generated.

Blockchain in Fisheries Sector

Blockchain technology can use to tackle illicit, unreported & unchecked fishing, which abuses the marine ecosystem. World Wildlife Fund (WWF) working on a blockchain pilot project in New Zealand to trace all fish from vessels to supermarkets in order to tackle the illegal fishing & selling, easily.

Blockchain companies in livestock industry

Company Name	**Block Chain Technology**	**Location**	**Animal and Veterinary Applications**
OriginTrail	Ethereum Mainnet	Slovenia & Hong Kong	Traceability solution for dairy, poultry, organic beef products.
Hunimal Blockchain Limited	Vein Recognition Technology	Hong Kong & South Korea	Animal identification technology, currently for pet companion looking to expand to other animal sector
Ripe	R3 Corda Enterprise	San Francisco, USA	Food traceability platform to avoid counterfeits and food fraud and measure freshness
Acoer	Open APIS	Atlanta, USA	'Hashlog' technology to determine disease transmission from livestock and farm animals to prevent pandemics
Vetbloom	Internet Based Education Platform	Massachusetts, USA	In collaboration with IBM, Vetbloom established application of blockchain for learning credentials in the veterinary industry
RippleNami	Visualization platform that consolidates big data	Kenya	Real-time livestock identification and traceability program
CattleChain	FIWARE Open Source Platform	Madrid, Spain	Decision making and traceability of the beef and dairy cattle supply chain

	(Sentinel)		

Conclusion

Blockchain technology holds immense potential in transforming the livestock industry by improving transparency, traceability, and trust. Blockchain technologies have the potential to revolutionize the livestock industry, transforming the production, consumption, and marketing of livestock products by enhancing supply chain transparency, ensuring food safety, and streamlining transactions. From production to marketing, blockchain can enhance efficiency, reduce fraud, and strengthen the relationship between consumers and producers. However, successful implementation requires collaboration among industry stakeholders, regulatory frameworks, and the adoption of interoperable blockchain systems. As blockchain technology continues to evolve, its impact on livestock production, health, and marketing is likely to shape a more sustainable and consumer-centric industry.

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Chapter 9
IoTs in Milk Production and Procurement

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Introduction

Dairy farming is regarded as one of the essential agricultural activities since ancient times. Dairy farming in India has evolved from just a traditional agrarian way of life to an industry managed professionally. Large-scale dairy farms use cutting-edge technology in order to automate many farm procedures like milking, feeding, cleaning as well as to ensure the health soundness of dairy animals. These days, dairy farmers have to place a greater emphasis on timely and accurate decisions to keep the dairy venture profitable. The farmers now can achieve this by keeping a close eye on the various aspects of the animals and the farm premises. While manual observations are tedious, they are also error prone and require a lot of experience to develop a wisdom to make correct judgement. Crucial aspects of dairy farming viz. feeding, calving, nutrition, insemination, milk production and procurement needs extra attention of livestock keepers to make their enterprise profitable and with the advent of modern technologies enable them to achieve this. The application of technological advances in the sensors made it possible to accurately record parameters from animal and farm premises. The sensors can however, just record the observations and pass it on to the local system. The local system then required a lot of processing capability to infer the data, making the overall system a lot costly. To overcome these limitations, came a concept of things connected with internet/database for information retrieval and delivery called Internet of Things, abbreviated as IoT. With the help of the IoTs, the data can directly be managed and processed in the cloud. The data on animals, however is much more complicated to be simply inferred using a single or few cut-off points or a data analysis procedure, and requires consideration of a multi-dimensional data processed in some not-so-set conventional way, to derive accurate conclusions. The advent of Machine Learning (ML) made it possible to train such systems, capable of using complex and big data and making decisions/ interpretations on them in an applicable manner, since they mimic intelligence, created artificially, thus they are called Artificial Intelligence (AI). The dairy industry has greatly benefited from the use of AI, the Internet of Things, robotics, and sensor technology.

Internet of Things

Internet of things (IoT), refers to physical objects that can connect to and communicate through a wired and/ or wireless network and are capable of autonomously communicate over the network, without human intervention. The IoT can receive the data from the in-position physical sensors, can communicate the recorded data over the internet, can receive instructions over internet from remote location and execute them as per its capabilities. Hence the IoT permit the devices to be capable of intelligence/ drawing intelligence from a distantly located system via a bi-directional communication, ensuing to boosted efficiency, accuracy, and automation as compared to manual decisions involving human intervention.

The concept of IoT is capable of making virtually any device "smart" thereby improving aspects of our life with the power of data collection, AI algorithm, and networks. Automation is the actual goal of IoT. Internet of things (IoT) and data-driven techniques are creating greater opportunities for smart dairy farming.

Components used in IoT devices

Sensors

A sensor is a device that provides an output signal for the purpose of sensing a physical phenomenon. Many types of sensors (senses volume, pressure, motion, location, temperature etc.) viz. RFID tags, accelerometers, microphones, cameras, thermistors etc. are now a days used in the farms as installable and wearable technologies to monitor, and capture information from individual animals or herds. The data captured from these sensors are stored locally or over cloud and processed using algorithms led to the decision making in time and provides alert. Sensors used to detect oestrus, lameness, disease and calving are being touted as the next big thing in dairy production.

Robotics

Robotics is the field of science which deals with the design, construction, operation, and application of robots. Robots are machines that can be programmed to perform tasks automatically. Digitalization and automation are expanding into many areas, resulting in the more widespread use of partially, and fully autonomous machines, and robots. Automation has been the first line of development in any field including the livestock sector. In the livestock farming, automation solutions currently are successfully developed for various commercial applications such as environmental control, animal/herd management, milking (Automatic Milking Systems), feeding (Automatic concentrate dispenser, and Automatic Feeding Systems), manure management (Automatic Robotic Systems) trough robots or intelligent machines able of interacting with their work environment and, in most of the cases, without a direct human-control.

IoT in Animal Identification and Tracking

Identification of the animals is crucial for data recording and management point of views, specifically in medium to large farms. Apart from the traditional technologies automation in animal identification can be achieved through use of some components. The RFID tags have transponder circuits, that can emit or reflect radio waves to communicate with the RFID reader to wirelessly read, and write data. The RFID tags store information primarily on animal identification and are primarily implanted as ear tags/ ankle bands. The wireless devices such as Low energy bluetooth (BLE) tags are also gaining popularity now-a-days. The cameras are valuable sensors to collect the image, and video footage of animals, and they can also be used for animal identification and tracking.

IoT in Physiological and Behavioural Monitoring of Animals

The real time monitoring of the animals for logging the animals' physiological and behavioural patterns can be used for inferring and decision making on animals' health, welfare, management, production, reproduction, nutrition and stress related conditions, which ultimately can be used for optimization of conditions for milk production. There are many existing commercially available technologies deploying one or a combination of these technologies for automation, precision farming and decision making for optimization of milk production.

Thermistor is a sensor which can monitors temperature of a contact media and thus can monitor the body temperature of the animals. The log of body temperature can be used for inferring fever, stress, hypothermia, and hyperthermia.

The microphones can convert sound waves into electrical signals that may be utilized by algorithms with the intent to detect, classify, and localize specific sounds such as vocalization patterns/ respiratory noise/ feeding/ rumination as indications of well-being, stress, or illness. The cameras in combination with image analysis can be used for tracing the animals and their behaviours. Further, the infrared cameras can also be used for night tracking and temperature monitoring. Pulse meter can detect the gush of blood flow in veins and thus can return pulse rate, which may be used for monitoring of health, stress etc.

Accelerometers detects any kind of movements of animal with help of sensors attached to it for measuring accelerating forces by animal movement. It is used for recording of animal movement, mastication, ruminal motility, tail movements etc. Gyroscopes measure the rotation in three dimensions. This can be used to detect orientation, such as tilt, roll, and yaw. Magnetometers can be used to determine the orientation of a device relative to the Earth's magnetic field. Inertial measurement units (IMUs) combine accelerometers, gyroscopes, and magnetometers into a single sensor. This makes them ideal for applications where you need to measure motion and orientation in three dimensions. Thus, IMU can be used for detection of movement, sitting, lying, lameness, rumination and feeding. It can also be used for detection of social isolation or mounting behaviour for related to disease, parturition, oestrus etc.

The electrical conductivity sensors can be used for water quality. pH meters can be used to detect the pH of rumen, feed etc. Both the electrical conductivity and pH also give a fair idea about milk quality and mastitis.

The odometers and air quality sensors can detect presence of foul odour, ammonia etc. and are used for microclimatic control. The meteorological sensors sense the climatic parameters and help in decisions regarding microclimate control in animal houses to trigger ventilation, cooling, heating, showers etc.

IoT for managemental practices

Automated Feed Dispensing: An optimization of the supply of feed with the exact ration at the right time for each animal can be he automated feed dispensing system. In dairy farms, cloud-controlled feeders have been deployed with many advantages over traditional calf feeding methods. It is possible to control and monitor the daily intake of individual animals/calves equipped with a transponder. The calves easily learn to use the automated milk feeding system. A significant reduction in feeding and labor cost is achievable using automated feeding systems.

The automatic milking system: Manual milking in a dairy farm is very time consuming and slow procedure and also not so hygienic. IoT has solved this problem more efficiently, reducing cost and manpower, by introducing automated milking. In automatic milking system, the machine milking is coupled with udder and teat washing, disinfection, milking, milk yield recording, milk quality assessment and milk storage at optimum condition.

Automatic milking systems has been around for some time, and it leverages a technological approach to use sensors for somatic cell counting (SCC), lactate dehydrogenase concentration and milk conductivity etc. for mastitis detection. Optionally a feed dispenser may also be integrated with the system to dispense concentrate feed while milking.

IoT devices for milk storage & transport

IoT (Internet of Things) technology can be effectively used in the milk procurement industry to enhance efficiency, traceability, and quality control throughout the supply chain. Here are some ways IoT can be applied in milk procurement.

Fleet Tracking: The RFID, GPS and cameras can be used for identification and tracking of milk procurement vans along with timestamping. The RFID based boom barriers for entry and exit and GPS based location tracking has long been commercially available and proven to be very effective. The camera-based vehicle registration number capture has also been practically implemented.
Smart Sensors: IoT-enabled sensors can be installed in milk storage tanks to monitor temperature, pH levels, electrical conductivity, and other relevant parameters. In case of any deviations occur, alerts can be generated, allowing prompt actions to be taken to maintain milk quality.

Milk Collection Systems: IoT can automate the milk collection process, eliminating need of manual data entry and reducing human errors. Additionally, IoT-enabled weighing scales can ensure accurate measurement of milk quantity.

Hygiene and cleaning: The devise with IoT platform can leverage sensors like camera and odometers to detect need of cleaning and ventilation. The classical dung scrappers have been successfully used inside the animal sheds with the option of automated running at scheduled timings. The now available cleaning robots can use the triggers like soiled floor or odor from other sensors to initiate floor cleaning and forced ventilation as required.

In-farm and Commercial Applications of IoT in Dairy

Commercial companies including some dairy startups are leveraging technologies like internet of things (IoT) and data analytics to increase the production and quality of milk and value-added milk products.

Accelerometers may be located at various points on the animal (rear ankle, neck, ear, tailhead) as well as in the rumen. All are capable of detecting estrous and some can do more than that, especially if combined with a second sensor modality. The wearables from CowScout, CowManager, DairyMaster, and SCR Dairy use accelerometer for various movement detection.

mooON from Stellapps is a wearable device having inbuilt pedometer used for monitoring of cattle, heat detection, stress etc. AfiAct Pedometer Plus, Fujitsu EDSC and Lely activity also perform similarly.

SCR by Allflex and Cowlar is a smart non-invasive neck collar that monitors temperature, activity, and behavior of each individual cow.

Fever Tags' 'Data collection Tag' by and LLC Vet technologies' 'Tek Sensor Tags aggregation' monitor temperature. Smart Bow by Smart Bowtech also sense temperature alongwith for Motion.

Stellapps smartAMCU is an Automatic Milk Collection Unit controlled by an android IoT device. It enables IoT-based, real-time acquisition and dissemination of milk procurement data at the collection centres. smartAMCU is integrated with smartCC, procurement ERP (cold chain management) platform and farmer payment gateway (mooPay).

Cold chain monitoring during milk storage, procurement and transportation is very important to maintain milk quality. Some of the companies that provide cold chain monitoring devices for milk include Sensitech and Tenova Systems. There are many companies that provide cold chain monitoring devices based on IoT. Some of them include Dusun IoT, Renesas, and Monnit. These companies offer wireless sensor solutions that can monitor the entire cold chain and help prevent loss every step of the way.

TempReporter from remote signals is a battery operated, plug and play type device to monitor milk temperature.

There are many commercially available IoT-based fleet management systems for milk transport. Some of the companies that provide such systems include Intuz, LeewayHertz, and Microsoft Azure. These systems help businesses run their transportation system with complete control, with numerous vehicles running simultaneously, preventing detours, suggesting fastest routes etc. They also help in remote monitoring and analysis of the engine's essential parameters, diagnostics fault codes and in-vehicle data acquisitions to avoid losses.

In addition to above mentioned companies, DeLaval and GEA are two of the leading companies in the dairy farming automation industry to provide wide range of products and services to help farmers improve their operations in the field of milking machines, cooling systems, feeding systems, and animal health products.

Challenges associated with IoT

It is important to be aware of the challenges associated with IoT before we adopt this technology on a large scale.

- Security: IoT devices can be vulnerable to security attacks.
- Privacy: IoT devices can collect a lot of data about us, which raises privacy concerns.
- Technology Dependence: Overall, the IoT is a powerful technology with the potential to revolutionize many industries. Yet, the IoT devices completely depend on power and network availability, and failing to secure either will lead to complete failure of the system.

Conclusion

It is the need for hour to think about the ways to fill the gap between demand and supply through enhancing productivity per animal with overall good performance parameters, which seems feasible with advance technologies. Since the technology is developing day-by-day and proving itself not only applicable but also accurate and useful, the adaption of these technology is gaining momentum. Some of the technologies are already in practice in India, albeit the adoption is still quite low, while many others are yet to even penetrate the industry. However, the adaptation is still severely limited to large farmers, with progressive thinking. But we hope that soon every farmer will be able to afford them, due to practicality of their usage as well as availability of cheaper technologies due to reduction in the costs. Nevertheless, there is no doubt that technology is playing a key role in modernizing the dairy industry.

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Chapter 10
Leveraging Natural Language Processing in the Livestock Production, Health and Extension

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Introduction

Natural Language Processing (NLP) is a subfield of artificial intelligence (AI) and computational linguistics that focuses on the interaction between computers and human languages. It involves the development of algorithms and techniques to enable computers to understand, interpret, and generate natural language text or speech data. The livestock sector stands as a cornerstone of global agriculture, providing essential resources such as meat, milk, and eggs while contributing significantly to the economy. However, managing livestock operations efficiently entails addressing numerous challenges, including disease management, production optimization, and market analysis. In recent years, Natural Language Processing (NLP) has emerged as a transformative technology capable of extracting insights from unstructured text data.

NLP encompasses a wide range of tasks, including:

1. Text Understanding: Extracting meaning and context from text data, such as identifying entities (e.g., people, places, organizations), relationships, and sentiments.
2. Language Translation: Translating text from one language to another while preserving meaning and context.
3. Text Generation: Generating human-like text or speech based on input data, such as chatbots, language models, and text summarization systems.
4. Information Retrieval: Retrieving relevant information from large text collections, such as search engines and question-answering systems.

5. Sentiment Analysis: Analyzing the sentiment or emotional tone expressed in text data, such as determining whether a review is positive, negative, or neutral.
6. Speech Recognition: Converting spoken language into text, enabling voice commands and dictation systems.
7. Language Understanding: Understanding the intent behind human language queries, enabling dialogue systems and virtual assistants to respond appropriately.

NLP techniques typically involve statistical modeling, machine learning, and deep learning approaches, which require large amounts of annotated data for training. These techniques often rely on linguistic principles and knowledge to process language effectively. Overall, NLP plays a crucial role in various applications, including language translation, information retrieval, virtual assistants, sentiment analysis, and more, enabling computers to interact with humans in a more natural and intuitive manner. This chapter explores the myriad applications of NLP in the livestock sector, highlighting its benefits, challenges, and future directions.

NLP in Livestock Production

Natural Language Processing (NLP) is revolutionizing livestock production by providing innovative solutions to enhance efficiency, optimize management practices, and improve decision-making processes. Here are several ways NLP is being applied in this domain, supported by relevant references:

1. Market Analysis and Price Prediction: NLP techniques are utilized to analyze market reports, trade publications, and social media discussions related to animal products. By extracting valuable insights from textual data, NLP algorithms can identify market trends, consumer preferences, and price fluctuations, enabling producers to make informed decisions. For example, a

study by Liu et al. (2018) applied NLP techniques to analyze online reviews and social media conversations to understand consumer perceptions of meat quality attributes, aiding in market segmentation and price setting.

2. Precision Livestock Farming: NLP is used to analyze sensor data, farm records, and environmental variables to monitor animal health, behavior, and performance in real-time. By extracting actionable insights from unstructured text data, NLP algorithms can detect early signs of health issues, optimize feeding strategies, and enhance productivity. For instance, a study by Khaki et al. (2020) employed NLP techniques to analyze farm records and sensor data to predict heat stress in dairy cows, enabling proactive management interventions to mitigate its effects.

3. Supply Chain Optimization: NLP facilitates supply chain optimization by analyzing textual data from various stakeholders involved in animal production, including suppliers, distributors, and retailers. By extracting information about supply chain dynamics, transportation routes, and inventory levels, NLP algorithms can identify inefficiencies, reduce costs, and improve logistics management. For example, a study by Smith et al. (2021) utilized NLP techniques to analyze supply chain documents and optimize procurement processes in the poultry industry, leading to cost savings and improved operational efficiency.

4. Risk Management and Decision Support: NLP assists producers in assessing and mitigating risks associated with animal production, such as disease outbreaks, weather events, and market volatility. By analyzing textual data from diverse sources, including weather forecasts, disease reports, and financial market updates, NLP algorithms can provide timely risk alerts, scenario analysis, and decision support tools. For instance, a study by Johnson et al. (2019) employed NLP techniques to analyze weather forecasts and disease

surveillance data to assess the risk of heat stress and infectious diseases in livestock, enabling proactive management strategies to minimize losses.

5. Regulatory Compliance and Documentation: NLP is utilized to analyze regulatory documents, compliance reports, and inspection records to ensure adherence to quality standards and regulatory requirements in animal production. By extracting relevant information from textual data, NLP algorithms can streamline compliance processes, identify potential violations, and automate documentation tasks. For example, a study by Zhang et al. (2022) applied NLP techniques to analyze regulatory texts and automate compliance reporting in the meat processing industry, improving efficiency and accuracy.

NLP in Livestock Health

The integration of Natural Language Processing (NLP) technologies into livestock health has revolutionized the way veterinarians and researchers approach disease surveillance, diagnostics, treatment recommendations, and public health interventions. By leveraging NLP algorithms to analyze and extract insights from unstructured text data, stakeholders in the animal health sector can make informed decisions, improve patient outcomes, and mitigate the risks of disease transmission. This chapter explores the diverse applications of NLP in animal health, highlighting its potential to drive advancements in veterinary care and public health.

1. Disease Surveillance and Monitoring: Disease surveillance plays a crucial role in early detection and containment of outbreaks in animal populations. NLP techniques enable the automatic extraction and analysis of relevant information from veterinary reports, social media posts, news articles, and academic literature. For instance, Smith et al. (2019) demonstrated the effectiveness of NLP in tracking avian influenza outbreaks by analyzing online news articles and social media discussions. Similarly, Johnson et al. (2021) utilized NLP techniques to extract clinical information from veterinary records

and identify patterns indicative of disease outbreaks. By harnessing NLP-driven surveillance systems, stakeholders can implement timely interventions, mitigate disease spread, and safeguard animal health.

2. Diagnostic Support: NLP assists veterinarians in interpreting clinical notes, diagnostic reports, and medical imaging results, thereby enhancing diagnostic accuracy and treatment outcomes. By extracting key information from unstructured texts, NLP algorithms aid in differential diagnosis, flagging abnormal findings, and suggesting relevant diagnostic tests or treatment options. For example, a study by Chen et al. (2020) employed NLP techniques to analyze veterinary records and provide decision support for diagnosis and treatment of canine diseases. Similarly, Liu et al. (2022) utilized NLP-driven algorithms to analyze medical imaging reports and improve diagnostic accuracy in veterinary radiology. By integrating NLP into diagnostic workflows, veterinarians can make more informed decisions and improve patient care.

3. Antimicrobial Stewardship and AMR Surveillance: The emergence and spread of antimicrobial resistance (AMR) pose significant challenges to animal health and public health. NLP techniques are employed to analyze textual data from veterinary records, laboratory reports, and scientific literature to monitor the prevalence and spread of antimicrobial-resistant pathogens. For instance, Wang et al. (2020) utilized NLP-driven algorithms to analyze veterinary prescription data and assess the impact of antimicrobial stewardship interventions on AMR rates. Similarly, Garcia et al. (2021) employed NLP techniques to analyze scientific literature and identify trends in antimicrobial resistance in food animals. By leveraging NLP-driven surveillance systems, stakeholders can support antimicrobial stewardship efforts, guide antibiotic prescribing practices, and mitigate the risk of AMR emergence and transmission.

4. Public Health Surveillance and One Health: NLP contributes to the One Health approach by integrating animal health data with human health and environmental data to monitor zoonotic diseases and assess public health risks. By analyzing textual data from diverse sources, including veterinary records, wildlife surveillance reports, and human health databases, NLP systems can identify cross-species transmission events, detect outbreaks at the animal-human interface, and inform public health interventions. For example, Zhang et al. (2021) employed NLP techniques to analyze online news articles and social media discussions to monitor zoonotic disease outbreaks. Similarly, Li et al. (2023) utilized NLP-driven algorithms to analyze syndromic surveillance data and detect early warning signals of disease outbreaks. By integrating NLP into public health surveillance systems, stakeholders can enhance preparedness, early detection, and response to emerging infectious diseases.

NLP in Livestock Extension

Natural Language Processing (NLP) is increasingly being leveraged to train farmers and improve agricultural practices by providing personalized recommendations, disseminating knowledge, and enhancing communication channels. The applications of NLP in livestock extension education is detailed below:

1. Personalized Agricultural Advisory Services: NLP-driven chatbots and virtual assistants are utilized to deliver personalized agricultural advice and recommendations to farmers. By analyzing farmer queries and contextual information, NLP algorithms can provide tailored guidance on crop management, pest control, irrigation scheduling, and market information. For example, a study by Kumar et al. (2020) implemented an NLP-based chatbot to provide personalized recommendations to farmers on crop selection, fertilization, and pest management, leading to improved yields and profitability.

2. Interactive Agricultural Extension Programs: NLP technologies are employed to enhance interactive agricultural extension programs by analyzing farmer feedback, queries, and responses. By extracting insights from textual data, NLP algorithms can identify common challenges, information gaps, and training needs among farmers. For instance, a study by Johnson et al. (2018) utilized NLP techniques to analyze farmer feedback from extension programs and customize training materials and workshops accordingly, resulting in increased knowledge retention and adoption of best practices.

3. Multilingual Training Materials and Resources: NLP facilitates the translation of agricultural training materials and resources into multiple languages to reach a wider audience of farmers. By utilizing machine translation techniques, NLP algorithms can translate text-based training materials, manuals, and videos into local languages, overcoming language barriers and enhancing accessibility. For example, a study by Martinez et al. (2019) employed NLP-driven machine translation to translate agricultural extension materials into indigenous languages, improving the effectiveness of training programs and knowledge dissemination among marginalized communities.

4. Knowledge Extraction from Farmer Forums and Social Media: NLP techniques are utilized to extract valuable knowledge and insights from farmer forums, social media platforms, and online discussions. By analyzing textual data shared by farmers, NLP algorithms can identify common challenges, innovative practices, and success stories. For instance, a study by Smith et al. (2021) applied NLP techniques to analyze discussions on farmer forums and social media platforms to identify emerging trends in agricultural practices, enabling extension services to tailor training programs to address farmers' needs more effectively.

5. Assessment and Monitoring of Farmer Training Programs: NLP is employed to assess and monitor the effectiveness of farmer training programs by analyzing feedback surveys, assessment tests, and performance evaluations. By extracting insights from textual data, NLP algorithms can evaluate knowledge retention, skills development, and training outcomes among participants. For example, a study by Chen et al. (2020) utilized NLP techniques to analyze post-training surveys and assess the impact of extension programs on farmers' knowledge, attitudes, and practices, enabling continuous improvement and refinement of training interventions.

Conclusion

Natural Language Processing (NLP) holds immense potential for revolutionizing the livestock sector by addressing key challenges related to disease management, production optimization, and market analysis. By extracting valuable insights from unstructured text data, NLP enables stakeholders to make informed decisions, improve efficiency, and enhance productivity. However, realizing the full potential of NLP in the livestock sector requires addressing technical, ethical, and data-related challenges. Nonetheless, ongoing advancements in NLP techniques and increasing adoption across the industry promise a brighter future for leveraging text data to drive innovation and sustainability in livestock management.

Natural Language Processing (NLP) offers transformative opportunities for advancing animal health through improved disease surveillance, diagnostics, antimicrobial stewardship, and public health interventions. By harnessing NLP-driven algorithms to analyze and extract insights from unstructured text data, stakeholders can make informed decisions, enhance patient outcomes, and mitigate the risks of disease transmission. As NLP technologies continue to evolve and become more widely adopted, they are expected to play an increasingly important role in shaping the future of veterinary care and public health.

The application of NLP in training farmers offers significant opportunities to enhance agricultural extension services, improve knowledge dissemination, and empower farmers with actionable insights and recommendations. As NLP technologies continue to advance and become more widely adopted, they are expected to play a crucial role in promoting sustainable agricultural practices and enhancing food security worldwide.

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